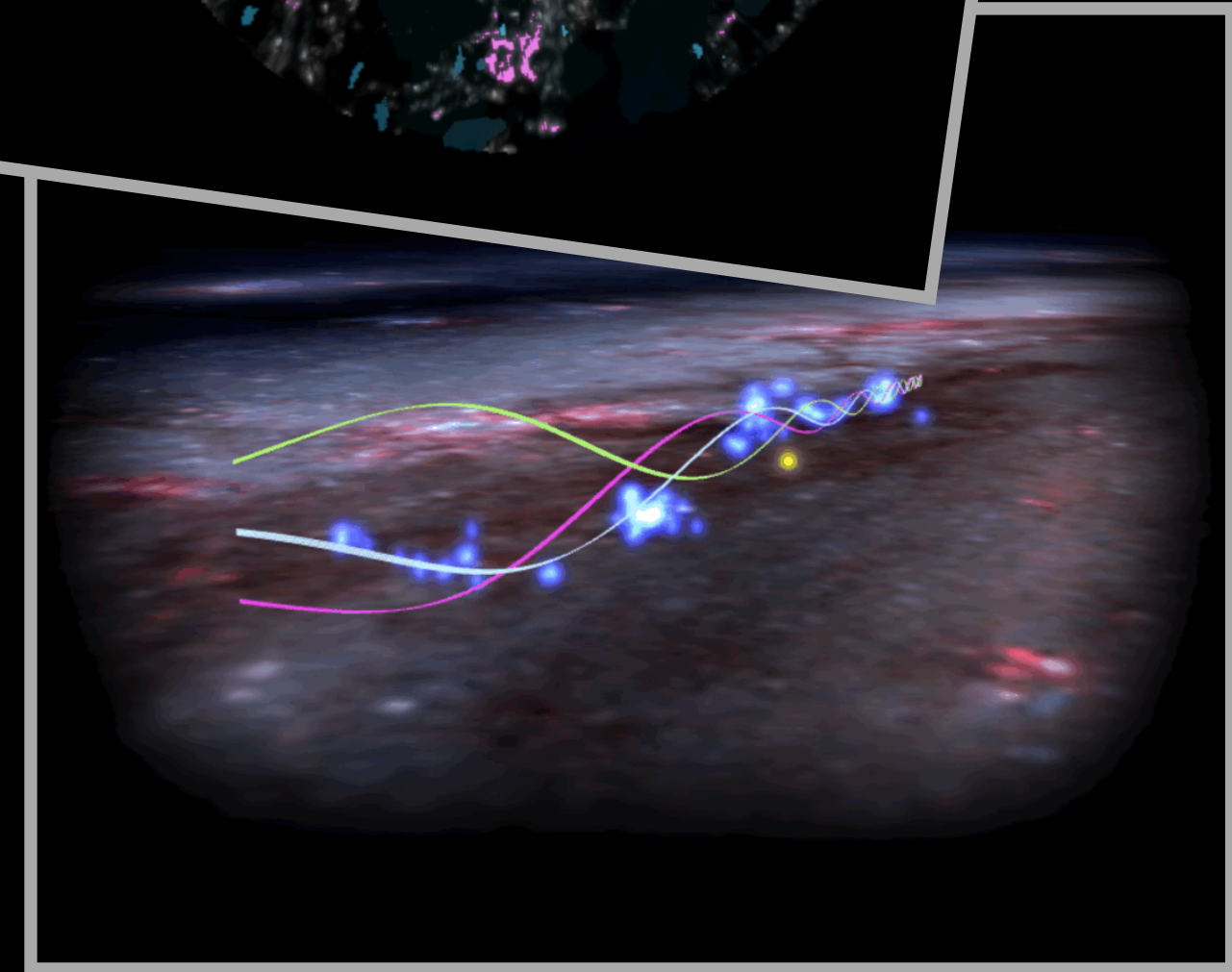
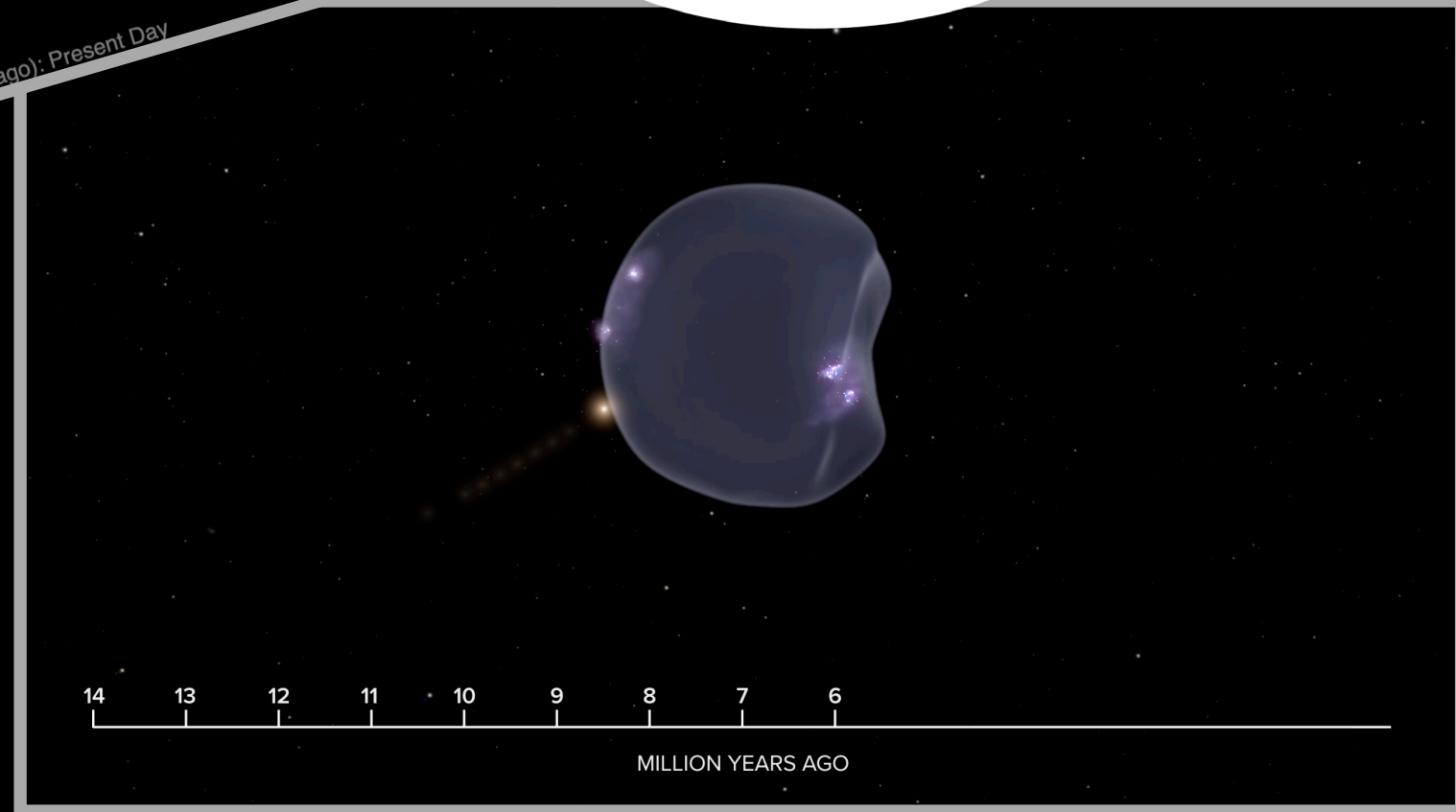
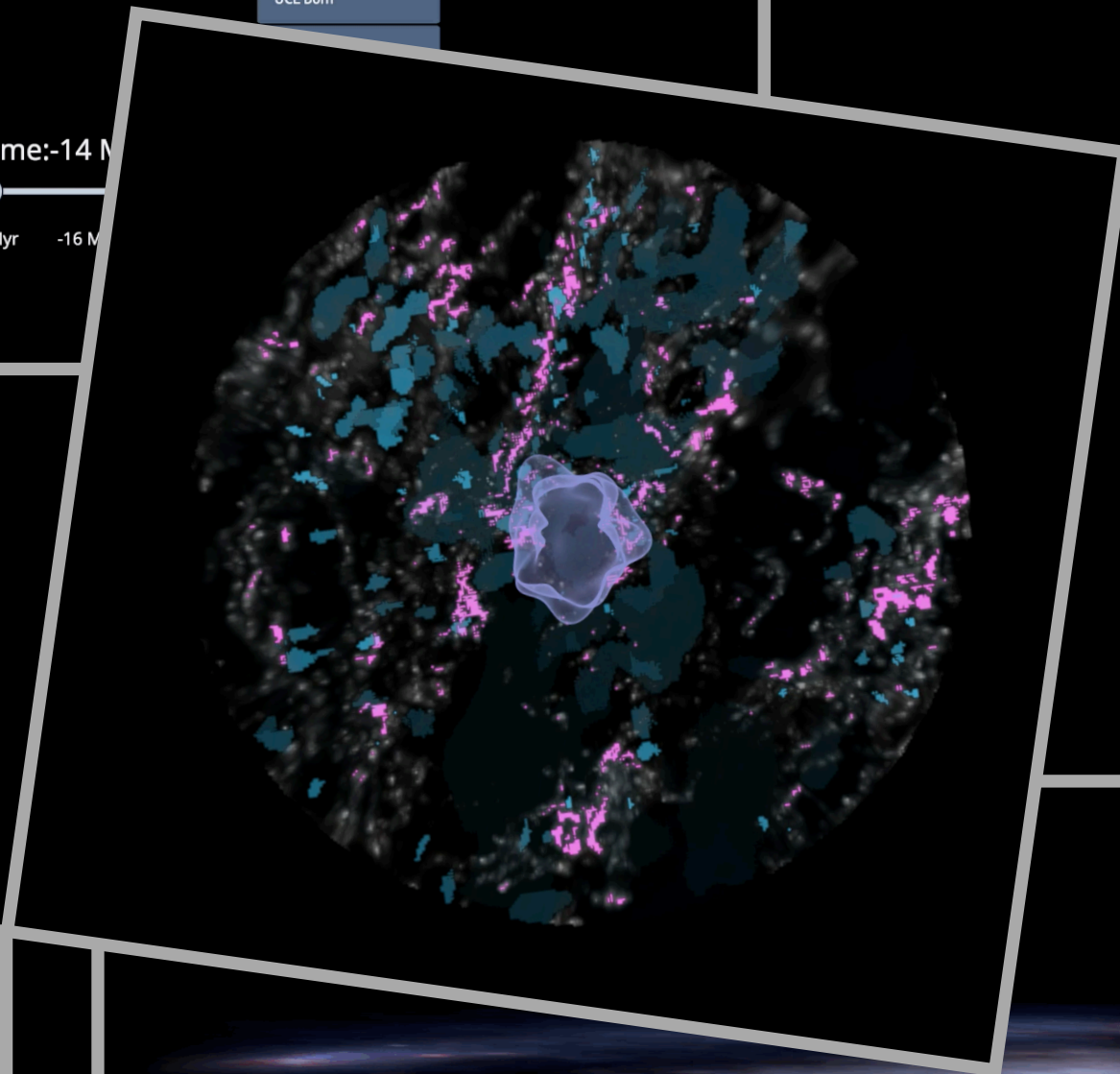


MILKYWAY3D.org



Zucker et al. 2021, Bialy et al. 2021; Zucker et al. 2022, Konietzka et al. 2024, O'Neill et al. 2024, Swiggum et al. 2024



AI in my Astro+Visualization Life Today*

Alyssa Goodman, Center for Astrophysics | Harvard & Smithsonian

*April 2025

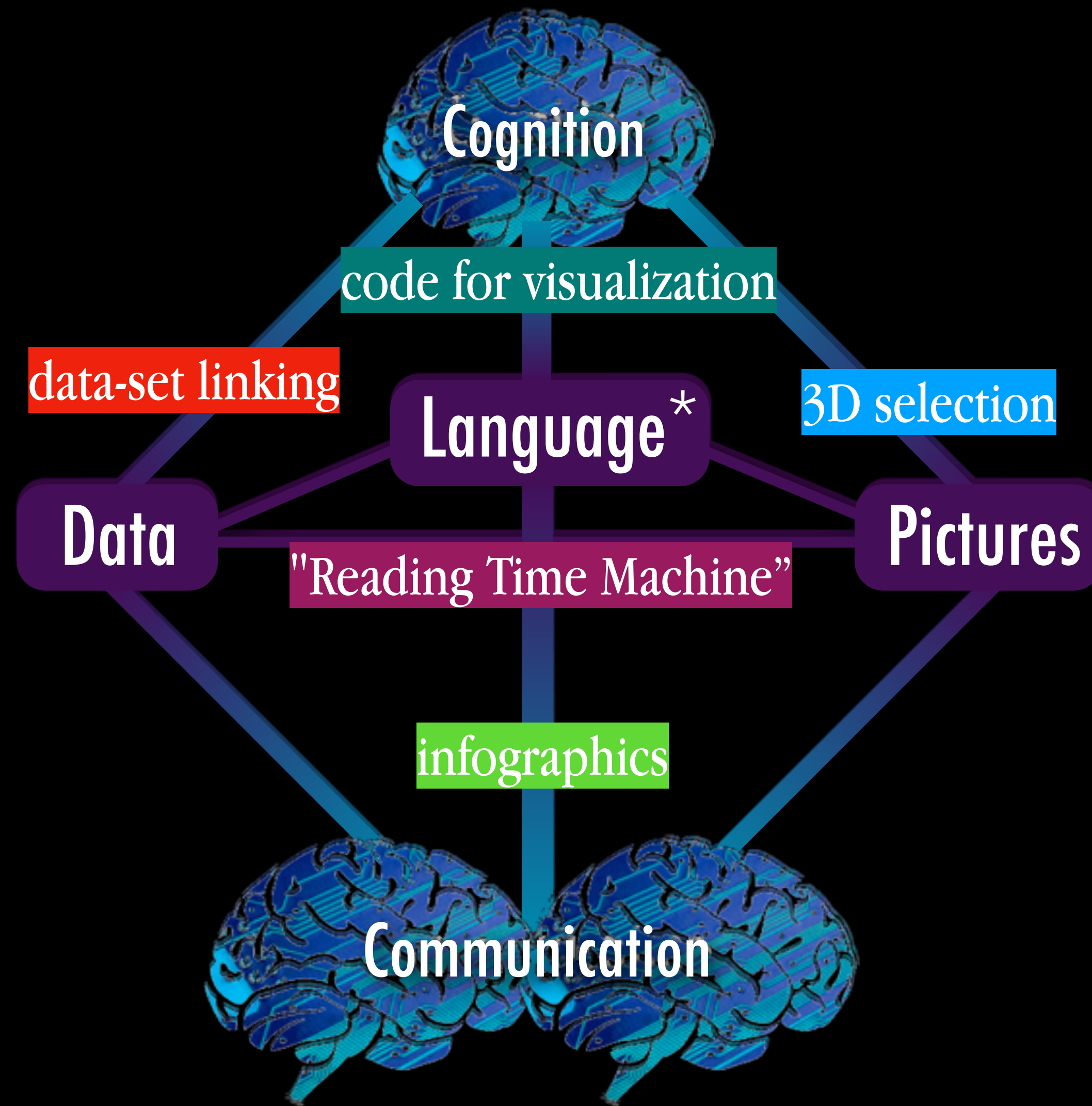
AI in my Astro + Visualization Life Today

I have been lucky enough in my career so far to watch, and I hope help, computational technology change what we can learn about our Universe. Today, in 2025, I somewhat unexpectedly find myself involved in a broad range of AI-based and AI-enhanced efforts designed to speed learning and discovery in astrophysics and in science. In this talk, I will offer glimpses into a handful of ongoing AI-enhanced efforts, each of which is very different from the others, yet which work together in a researcher/educator's life to speed progress. Work to be highlighted includes: 1) automated **data-set linking** in the "glue" and LIVE-Environments visualization environments; 2) The **"Reading Time Machine"** which uses AI to "read" graphics and images and ingest their content into the ADS Literature archive, as "data," 3) approaches to **3D selection** in volumetric data, using both AI and augmented reality (AR); 4) a quest to understand why LLMs are so good at describing **infographics**, but so terrible at creating them; 5) capabilities of AI for writing **code for visualization**, in both research and education. The plan of the talk will be to present an overview of each of these efforts, in order to inspire broader discussion of whichever topics evolve as most interesting to the assembled audience.

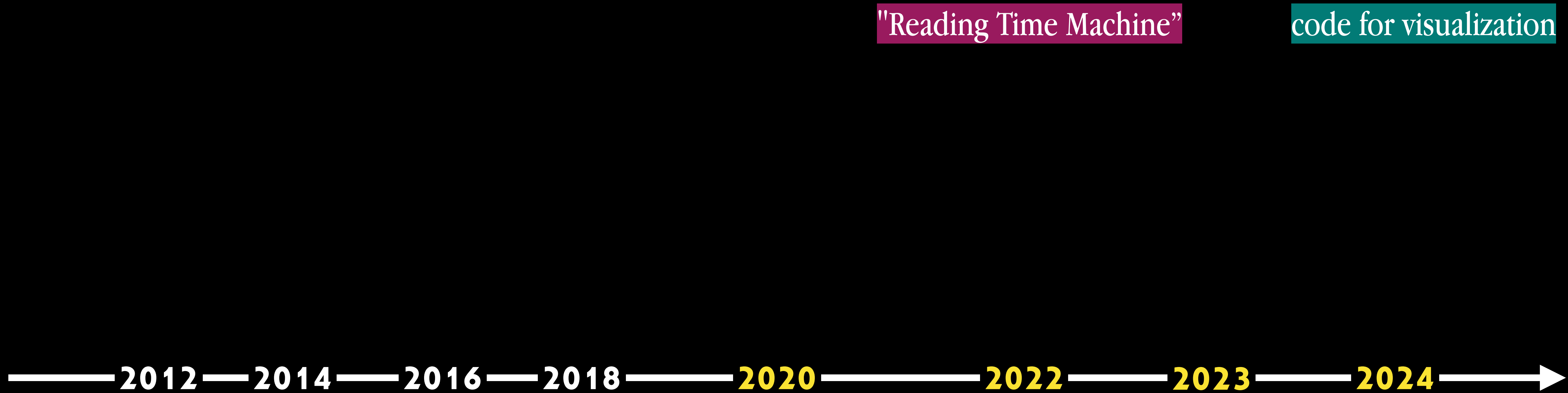
Thematic questions for discussion

1. visualization and infographics — how good is AI at abstraction, and how good will it become?
2. If we give “all” the MilkyWay3D.org data to AI, what (kinds of) new physical insights might we expect— should we have expectations *a priori*—or is that approach too restrictive? (Note, 3D dust also AI!)

AI in My Astro + Visualization Life TODAY



*"Language" includes words & math



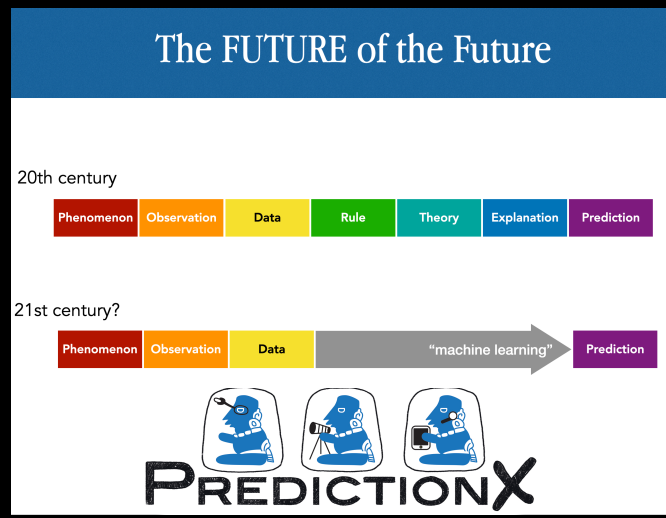
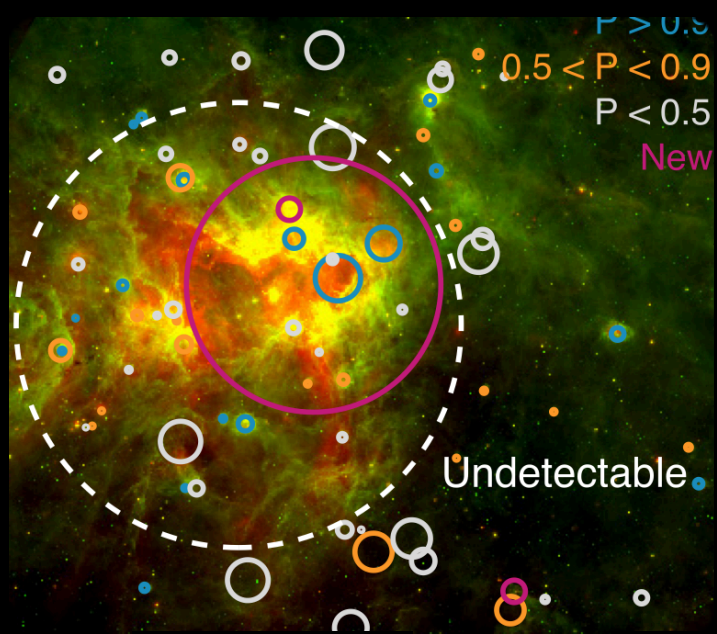
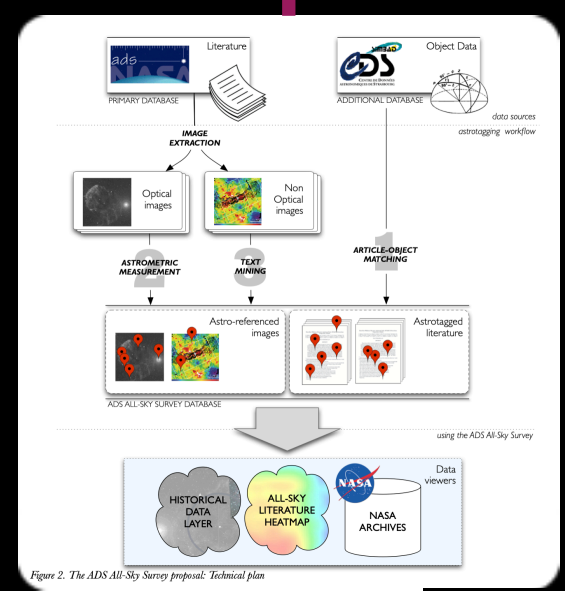
data-set linking

3D selection

infographics

"Reading Time Machine"

code for visualization



Reading Time Machine

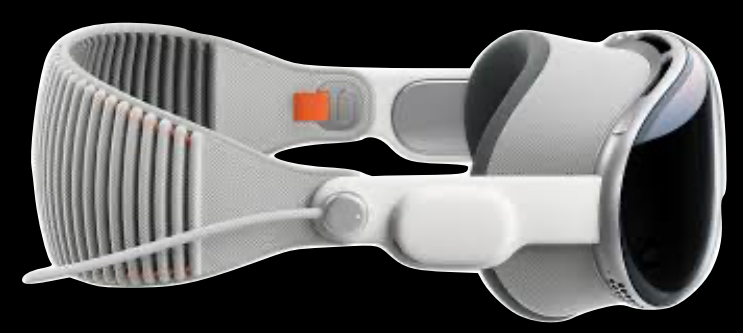
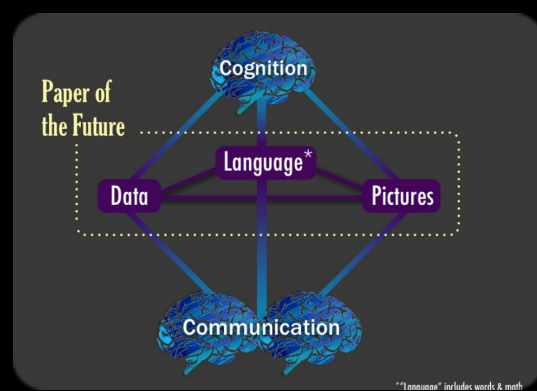
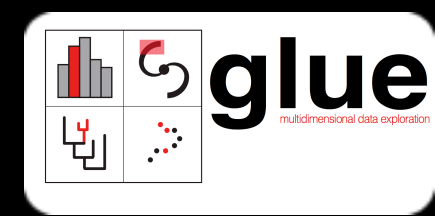
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data-set linking

3D selection

infographics

“State-of-the-Art” ML in 2014

THE ASTROPHYSICAL JOURNAL SUPPLEMENT SERIES, 214:3 (18pp), 2014 September
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doi:10.1088/0067-0049/214/1/3

THE MILKY WAY PROJECT: LEVERAGING CITIZEN SCIENCE AND MACHINE LEARNING TO DETECT INTERSTELLAR BUBBLES

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Received 2013 October 3; accepted 2014 June 7; published 2014 August 20

ABSTRACT

We present Brut, an algorithm to identify bubbles in infrared images of the Galactic midplane. Brut is based on the Random Forest algorithm, and uses bubbles identified by >35,000 citizen scientists from the Milky Way Project to discover the identifying characteristics of bubbles in images from the *Spitzer Space Telescope*. We demonstrate that Brut’s ability to identify bubbles is comparable to expert astronomers. We use Brut to re-assess the bubbles in the Milky Way Project catalog, and find that 10%–30% of the objects in this catalog are non-bubble interlopers. Relative to these interlopers, high-reliability bubbles are more confined to the mid-plane, and display a stronger excess of young stellar objects along and within bubble rims. Furthermore, Brut is able to discover bubbles missed by previous searches—particularly bubbles near bright sources which have low contrast relative to their surroundings. Brut demonstrates the synergies that exist between citizen scientists, professional scientists, and machine learning techniques. In cases where “untrained” citizens can identify patterns that machines cannot detect without training, machine learning algorithms like Brut can use the *output* of citizen science projects as *input* training sets, offering tremendous opportunities to speed the pace of scientific discovery. A hybrid model of machine learning combined with crowdsourced training data from citizen scientists can not only classify large quantities of data, but also address the weakness of each approach if deployed alone.

Key words: H II regions – ISM: bubbles – methods: data analysis – stars: formation

Online-only material: color figures

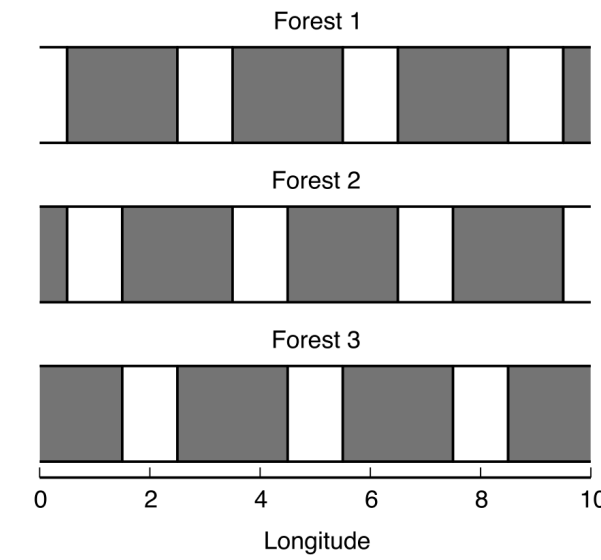


Figure 7. Illustration of the zones used to train each Random Forest. Each forest is trained using the data from the shaded regions in its zone, and used to classify the light regions.

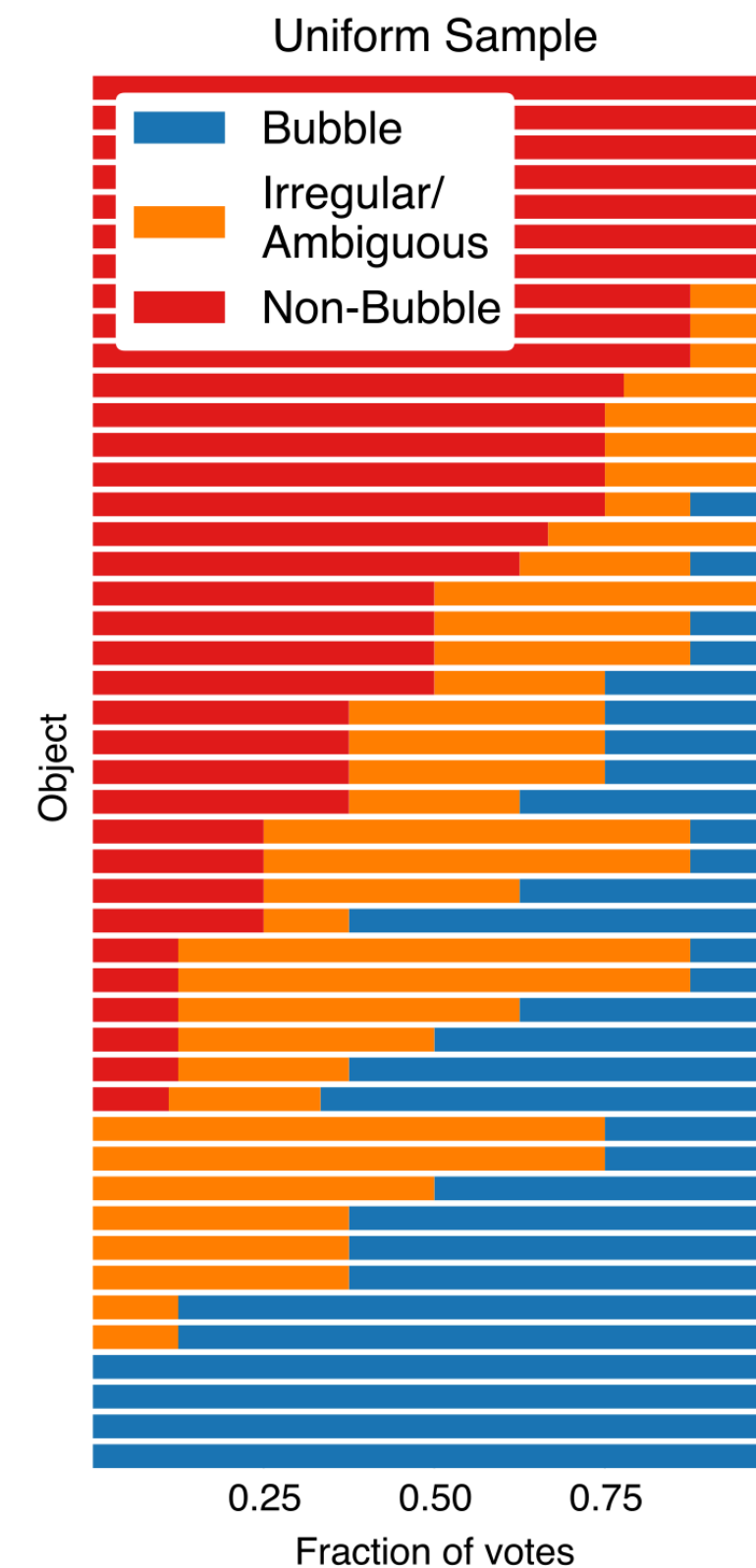


Figure 12. Same as Figure 10, for the uniform sample.

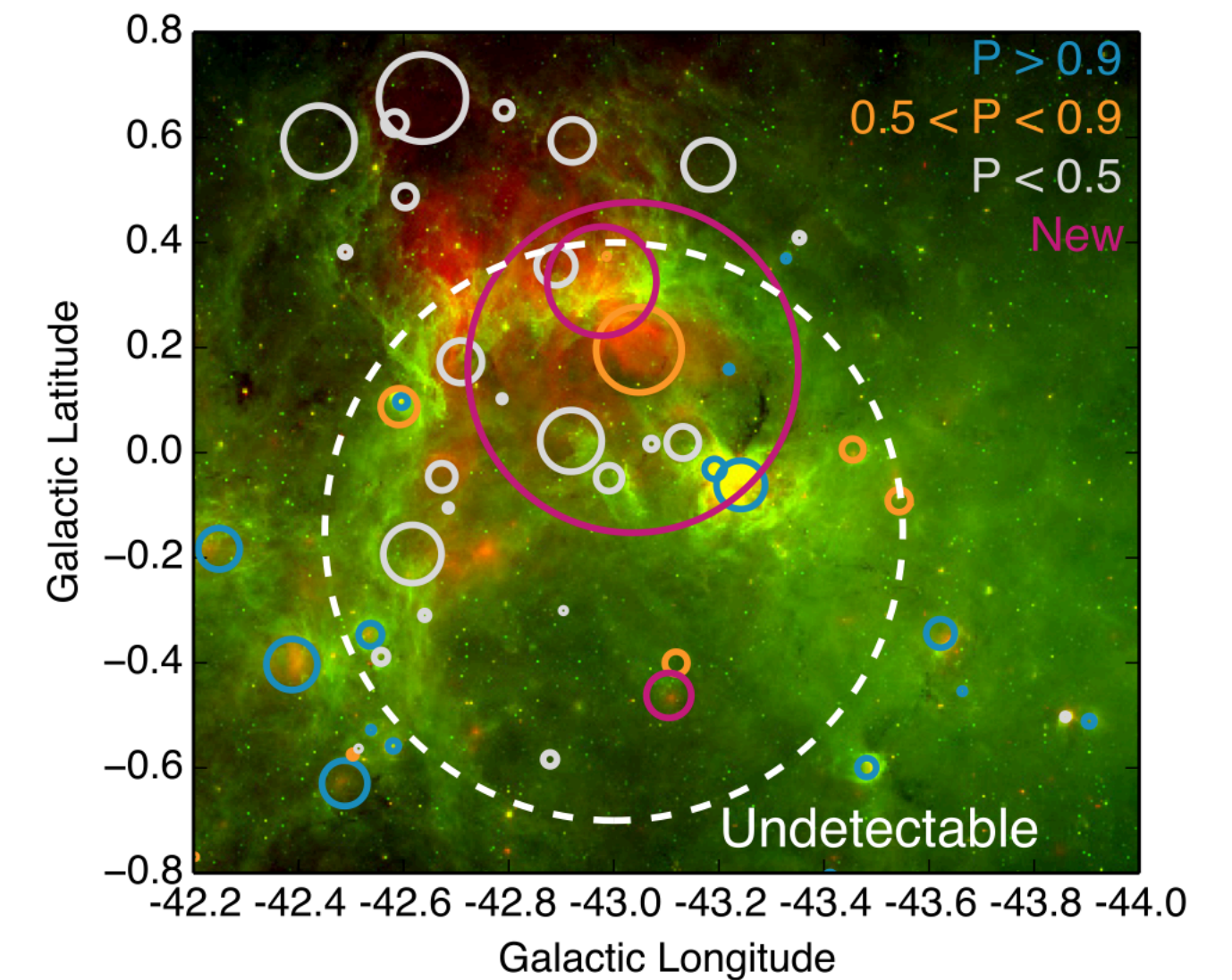
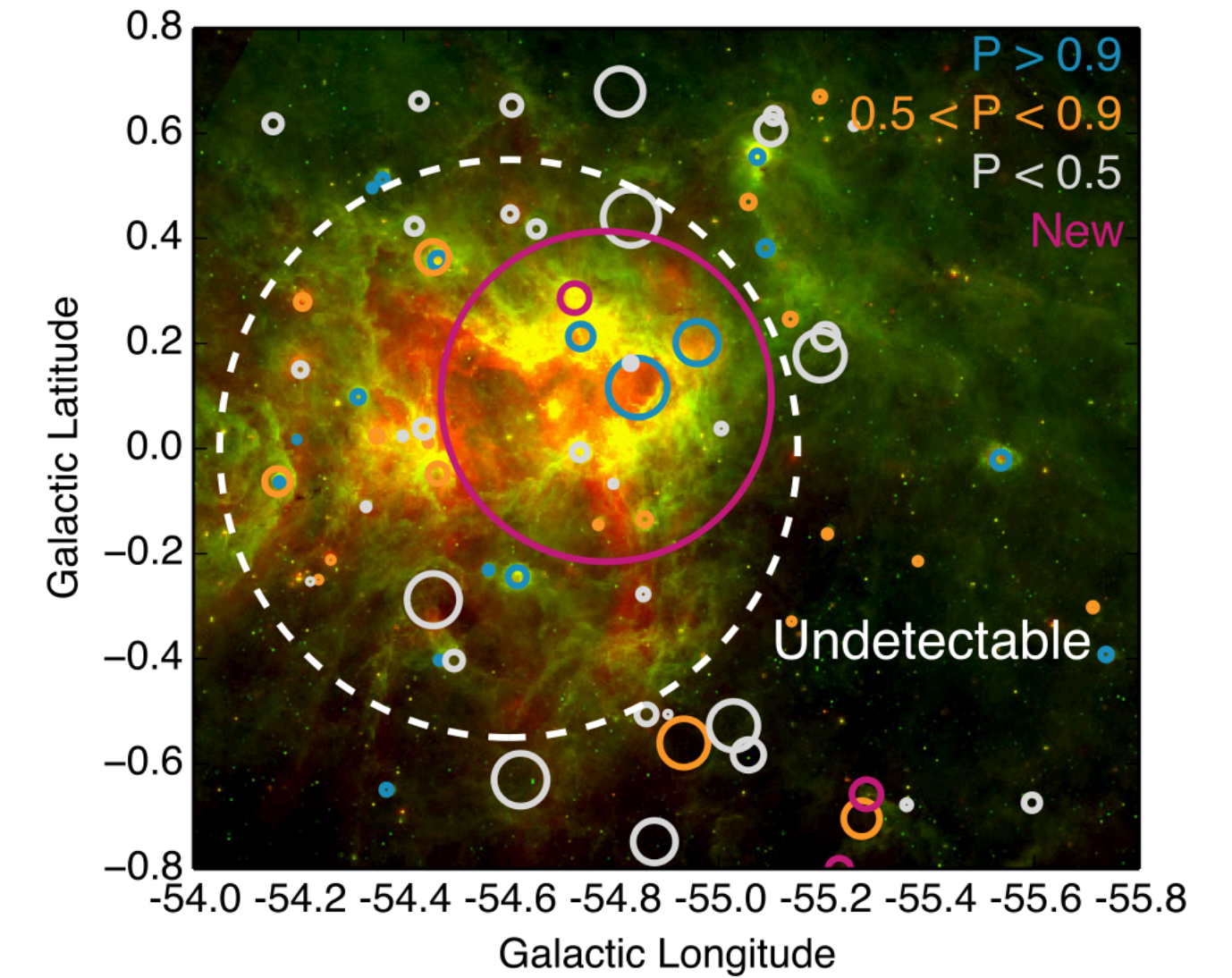
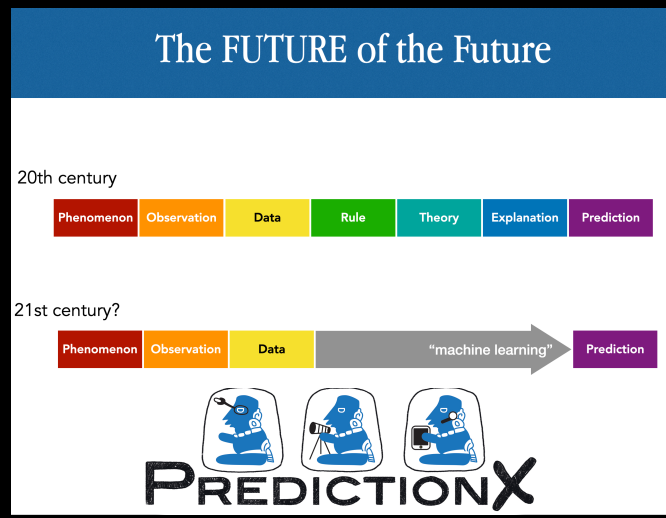
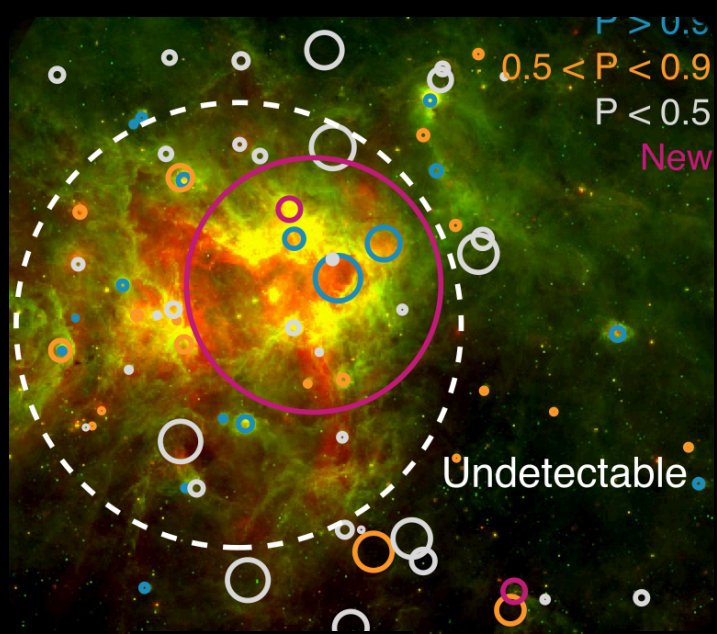
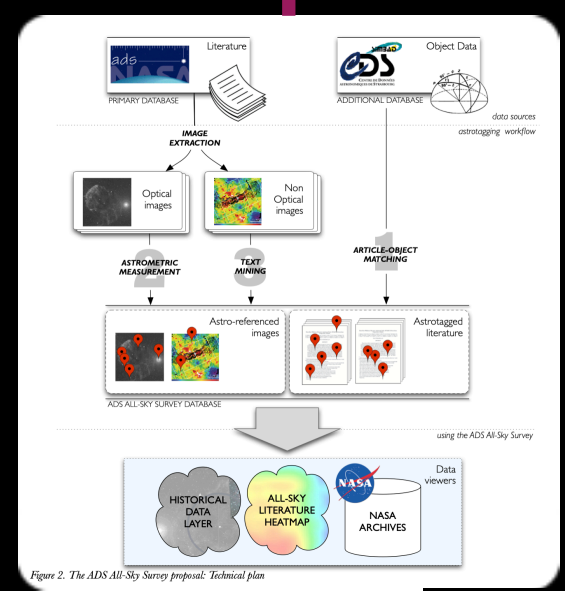


Figure 16. Two fields with overabundances of low-probability bubbles in the MWP catalog.

"Reading Time Machine"

code for visualization

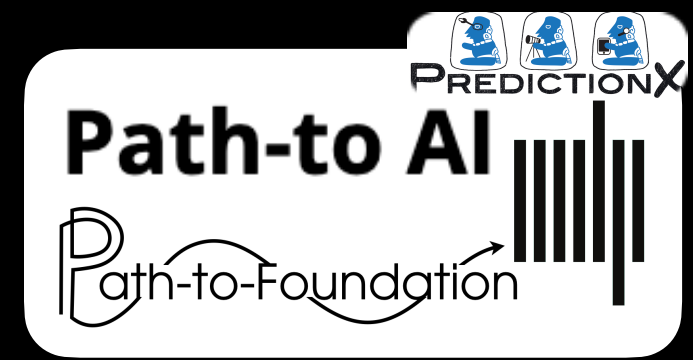


Reading Time Machine

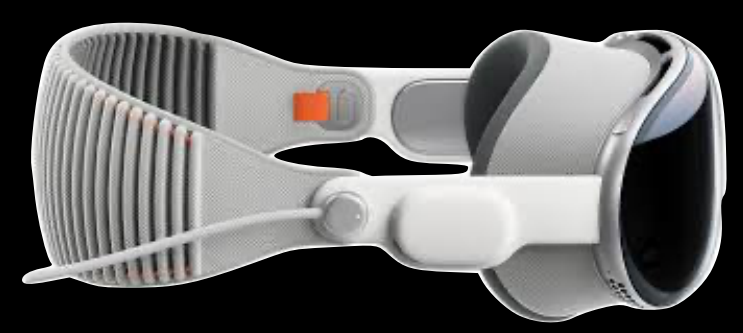
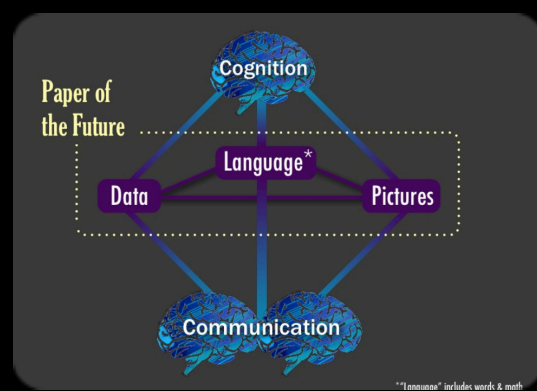
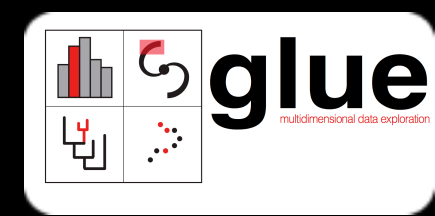
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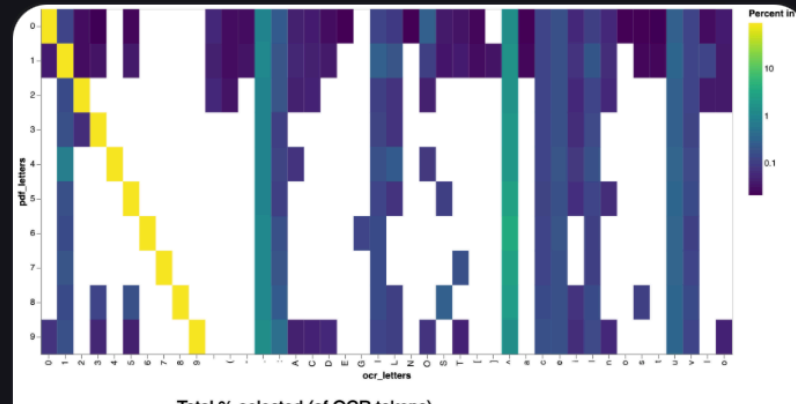
data-set linking

3D selection

infographics



Reading Time Machine



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The digitization of historical astrophysical literature with highly localized figures and figure captions

Jill P. Naiman^{1,2}  · Peter K. G. Williams³ · Alyssa Goodman³

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Abstract

Scientific articles published prior to the “age of digitization” in the late 1990s contain figures which are “trapped” within their scanned pages. While progress to extract figures and their captions has been made, there is currently no robust method for this process. We present a YOLO-based method for use on scanned pages, after they have been processed with Optical character recognition (OCR), which uses both grayscale and OCR features. We focus our efforts on translating the intersection-over-union (IOU) metric from the field of object detection to document layout analysis and quantify “high localization” levels as an IOU of 0.9. When applied to the astrophysics literature holdings of the NASA astrophysics data system, we find F1 scores of 90.9% (92.2%) for figures (figure captions) with the IOU cut-off of 0.9 which is a significant improvement over other state-of-the-art methods.

Keywords Scholarly document processing · Document layout analysis · Astronomy

RTM Project led by Jill Naiman, UIUC, funded by NASA ADAP

"Reading Time Machine"

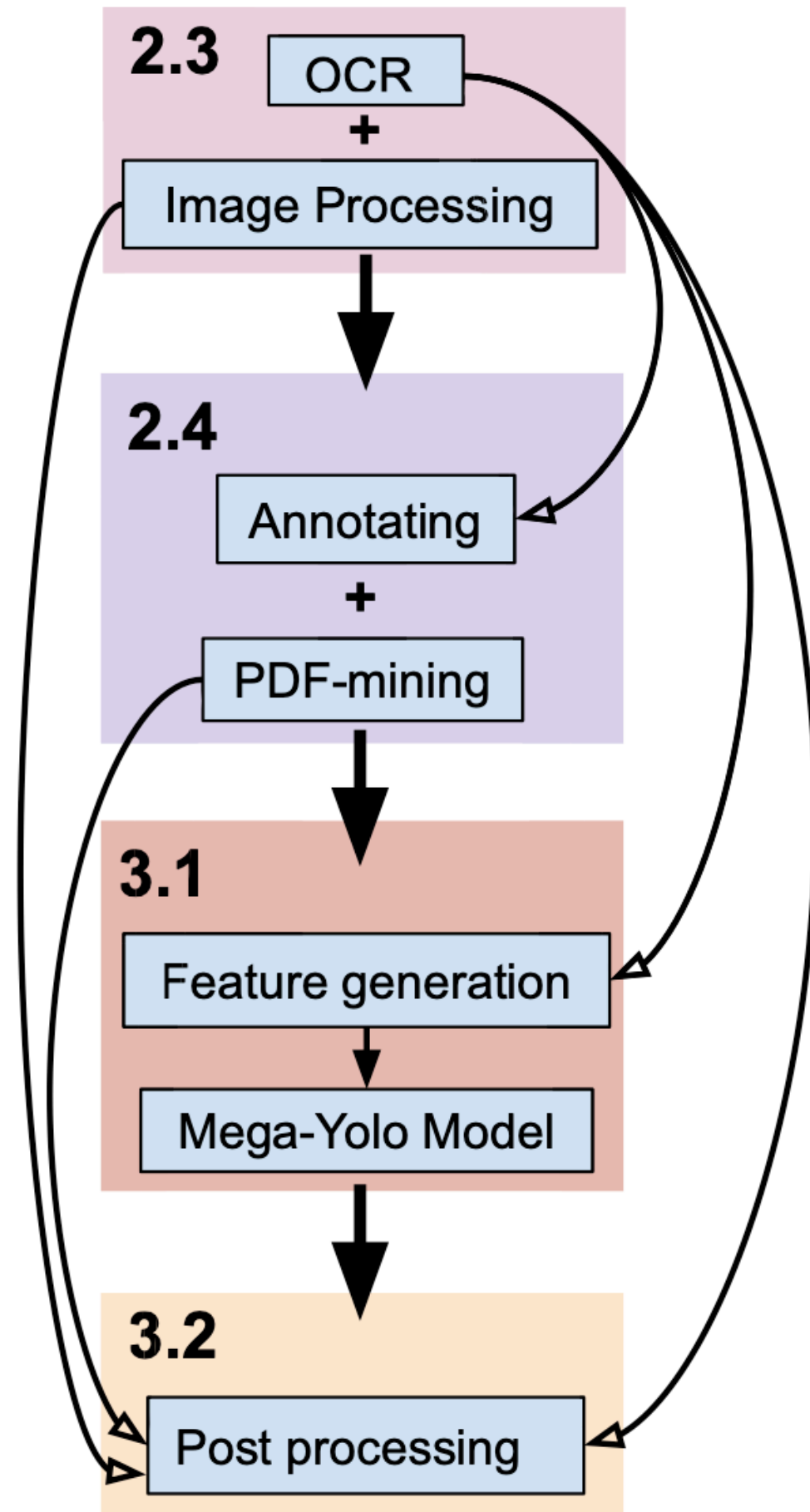
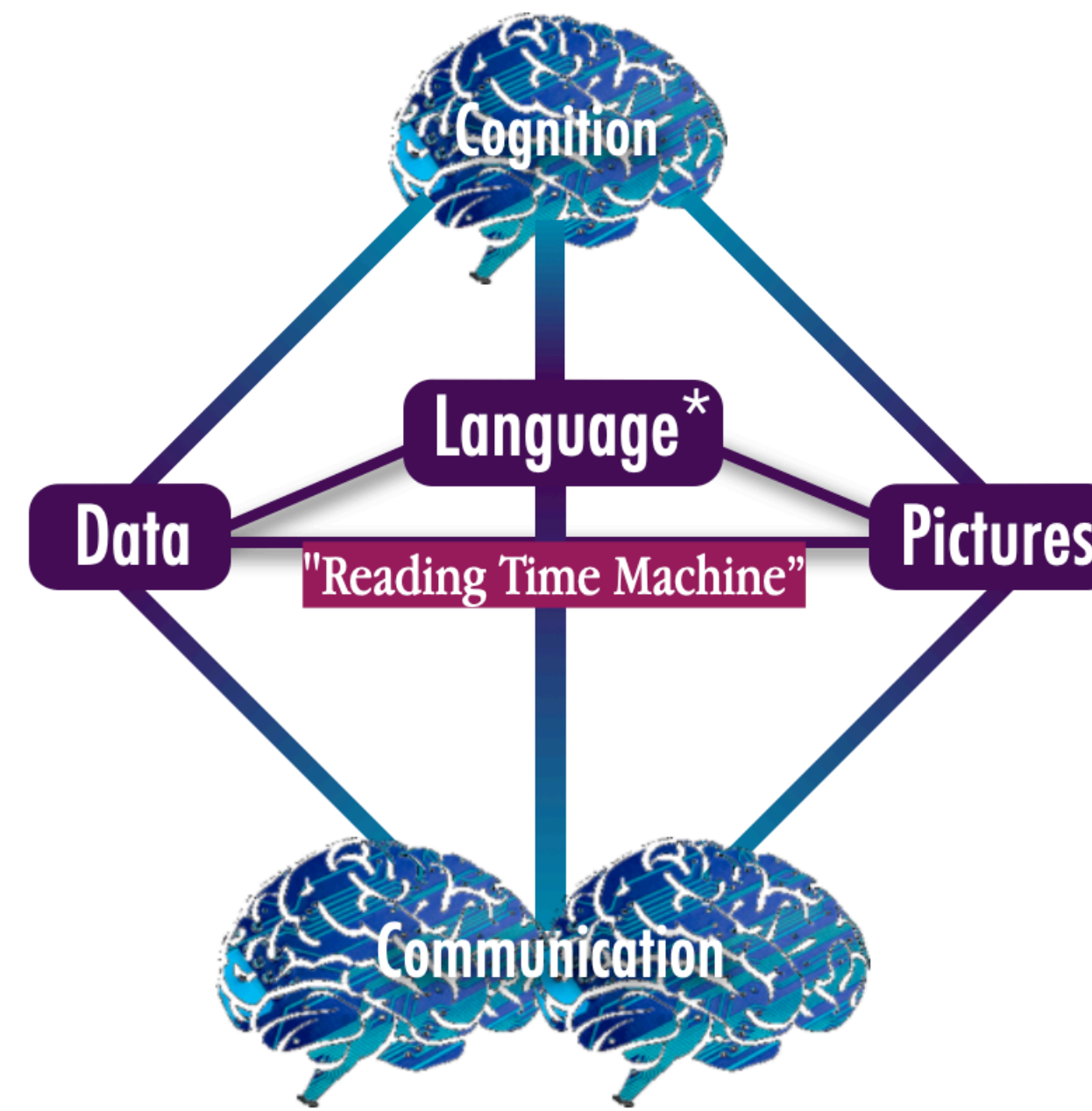


Fig. 3 Our overall pipeline is shown as four main steps. OCR and image processing is discussed in Sect. 2.3. Class definitions and “codebook”, along with annotations and PDF mining are discussed in Sect. 2.4. Feature selection and deep learning model description is housed in Sect. 3.1, and post-processing techniques are discussed in Sect. 3.2. (See Appendix 6 and Fig. 10 for a larger breakdown of these steps.)



The digitization of historical astrop

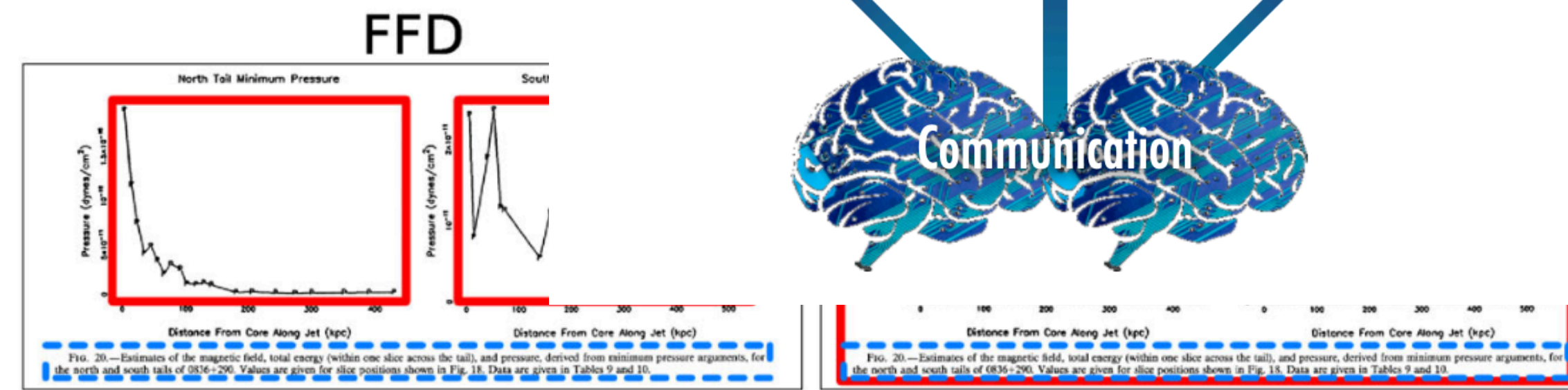


Fig. 4 Illustration of the “codebook” for defining figures and figure captions (right) in comparison with other works (left, center). For example, some works [e.g., [19]] (left red boxes) typically split subfigures into separate figures while other works [14,18,32] (center red box) combine figure captions and figures into a single “figure” box. Caption boxes (shown in blue) in other methods are delineated with dashed squares as

applications often focus on detection of figures alone [e.g., [32]]. Note as there is no overlap in datasets for direct comparison, the boxes from other works are shown for illustrative purposes only. See Sect. 4.2 for a comparison of our category definitions and methodology with a subset of several of these datasets (color figure online)

Large Synthetic Data from the arXiv for OCR Post Correction of Historic Scientific Articles

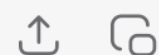
Authors: J. P. Naiman, Morgan G. Cosillo, Peter K. G. Williams, Alyssa Goodman | [Authors Info & Claims](#)

[Linking Theory and Practice of Digital Libraries: 27th International Conference on Theory and Practice of Digital Libraries, TPDL 2023, Zadar, Croatia, September 26–29, 2023, Proceedings](#)

Pages 265 - 274 • https://doi.org/10.1007/978-3-031-43849-3_23

Published: 26 September 2023 [Publication History](#)

ChatGPT 4o >



The paper **“Large Synthetic Data from the arXiv for OCR Post Correction of Historic Scientific Articles”** by Naiman et al. presents a new approach to improving the accuracy of **optical character recognition (OCR)** for **historic astrophysical literature**, particularly from the **NASA Astrophysics Data System (ADS)**. Here’s a concise summary:

🔍 Goal

To improve OCR accuracy for historical scientific texts by generating a **large synthetic dataset** from arXiv LaTeX source files, and using it to train deep learning models for **post-OCR correction**.

🔧 Methodology

- **Source:** Mined LaTeX files from ~65k arXiv astronomy papers (1991–2011); ~7,850 successfully aligned with OCR outputs.
- **Synthetic Ground Truth (SGT):** Created by marking words, equations, citations, and references in LaTeX source using the tikzmark package.
- **OCR Process:** Rendered PDFs were OCR’d using **Tesseract**.
- **Alignment:** An algorithm matched OCR output with ground truth via bounding box overlap and edit distance.
- **Dataset Size:** 1.5M sentence pairs with **203 million character-level alignments**.

🧠 Model Training

- Trained a transformer model (**ByT5**) on the dataset.
- Baseline results showed:
 - **67% improvement in Character Error Rate (CER)** and
 - **60% improvement in Word Error Rate (WER)** on synthetic data.

"Reading Time Machine"

- When tested on **real historic ADS data**, improvements were smaller but significant:

- **CER improved by 7.71%**
- **WER improved by 18.82%**

🏆 Key Contributions

- **Largest known scientific OCR post-correction dataset.**
- **Open-source tools** and **interactive dashboards** for exploration.
- **Generalizable pipeline** for other scientific domains with LaTeX sources.

⚠️ Limitations

- Not all arXiv articles compile successfully due to outdated LaTeX.
- Public sharing of full dataset is restricted (working with arXiv to resolve).
- More robust post-correction for ambiguous LaTeX constructs (like multiple representations of $\leq 90\%$) remains future work.

🔗 Resources

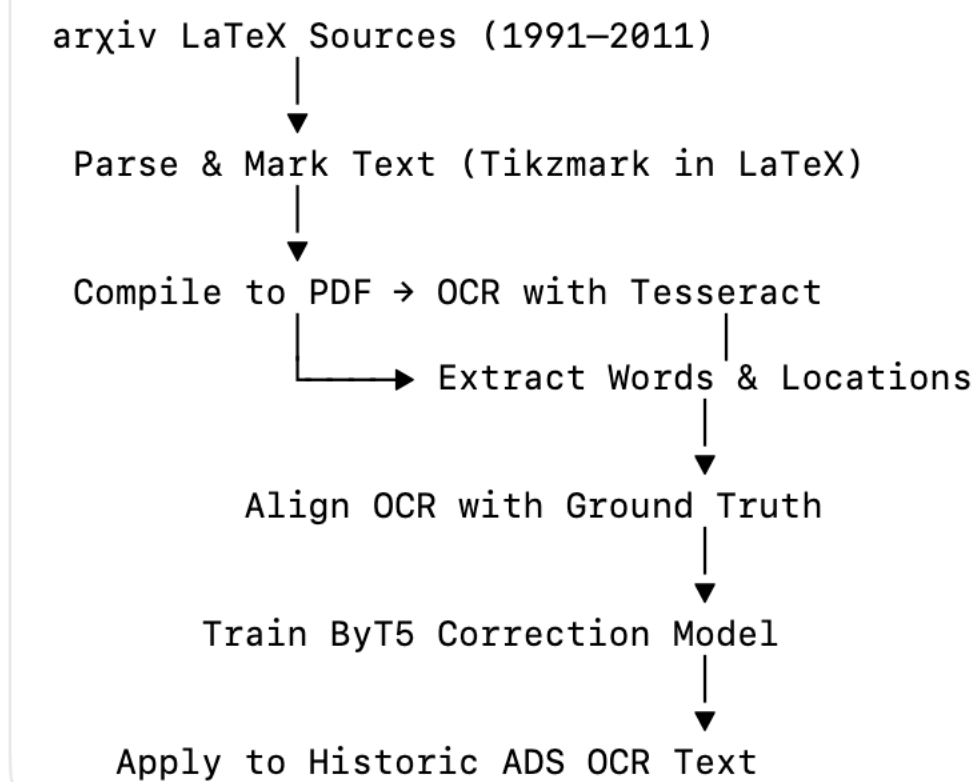
- Project site & dashboard: <https://readingtimemachine.github.io/projects/1-ocr-groundtruth-may2023>
- Code & subset of data: [GitHub repository](#)

Let me know if you’d like a shorter version, a diagram of the pipeline, or a breakdown of how this might apply to another field!



🔄 Diagram: OCR Post-Correction Pipeline

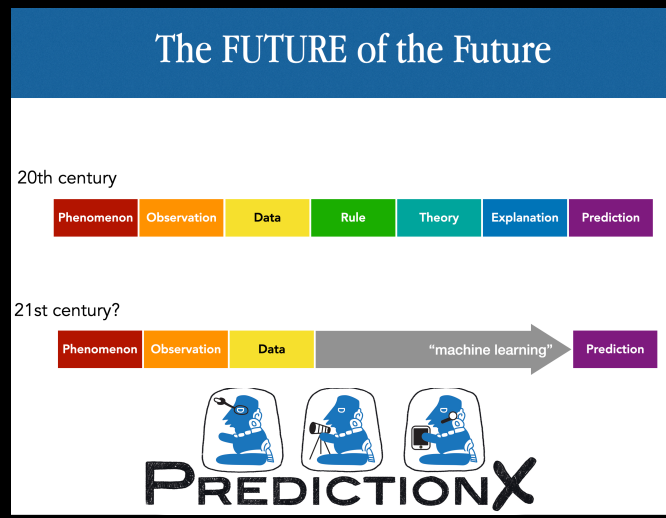
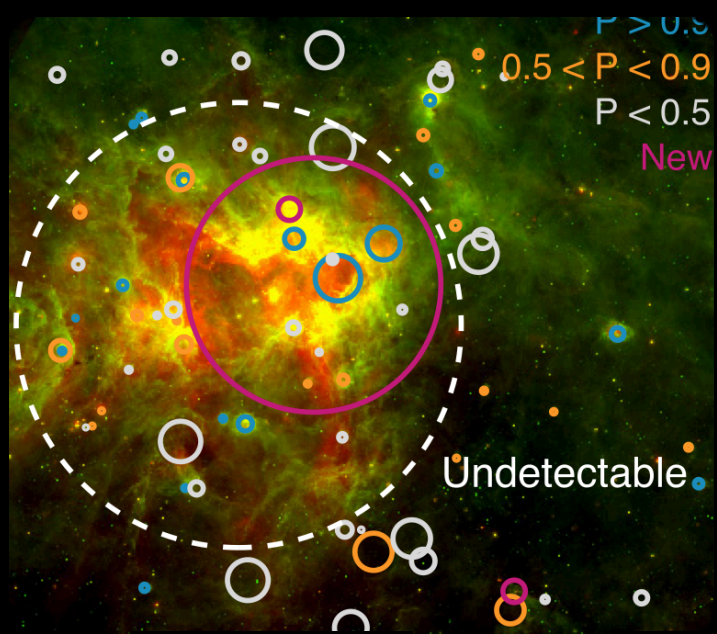
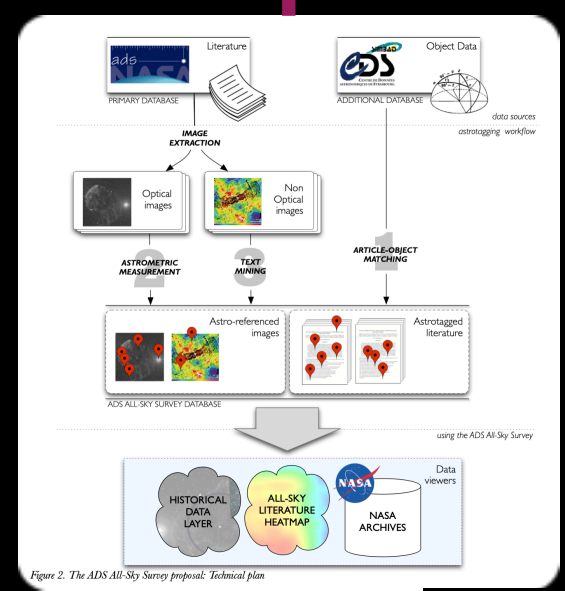
plaintext



RTM Project led by Jill Naiman, UIUC, funded by NASA ADAP

"Reading Time Machine"

code for visualization

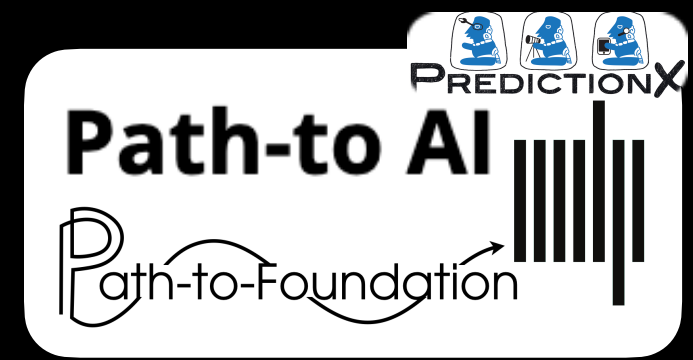


Reading Time Machine

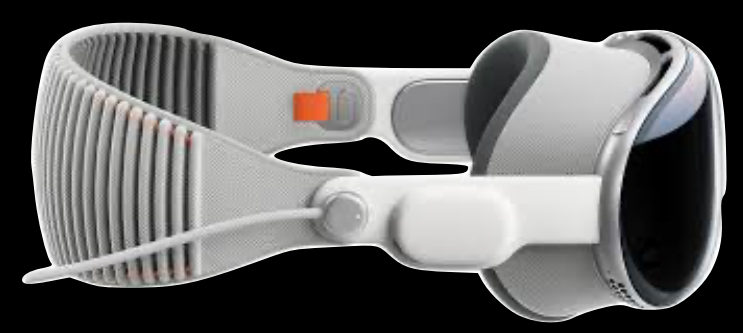
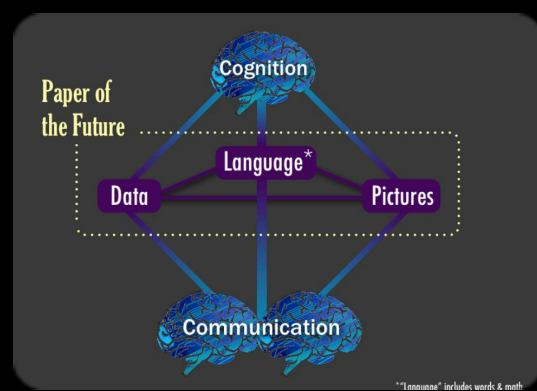
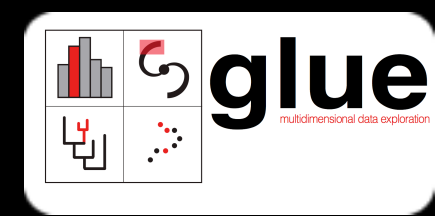
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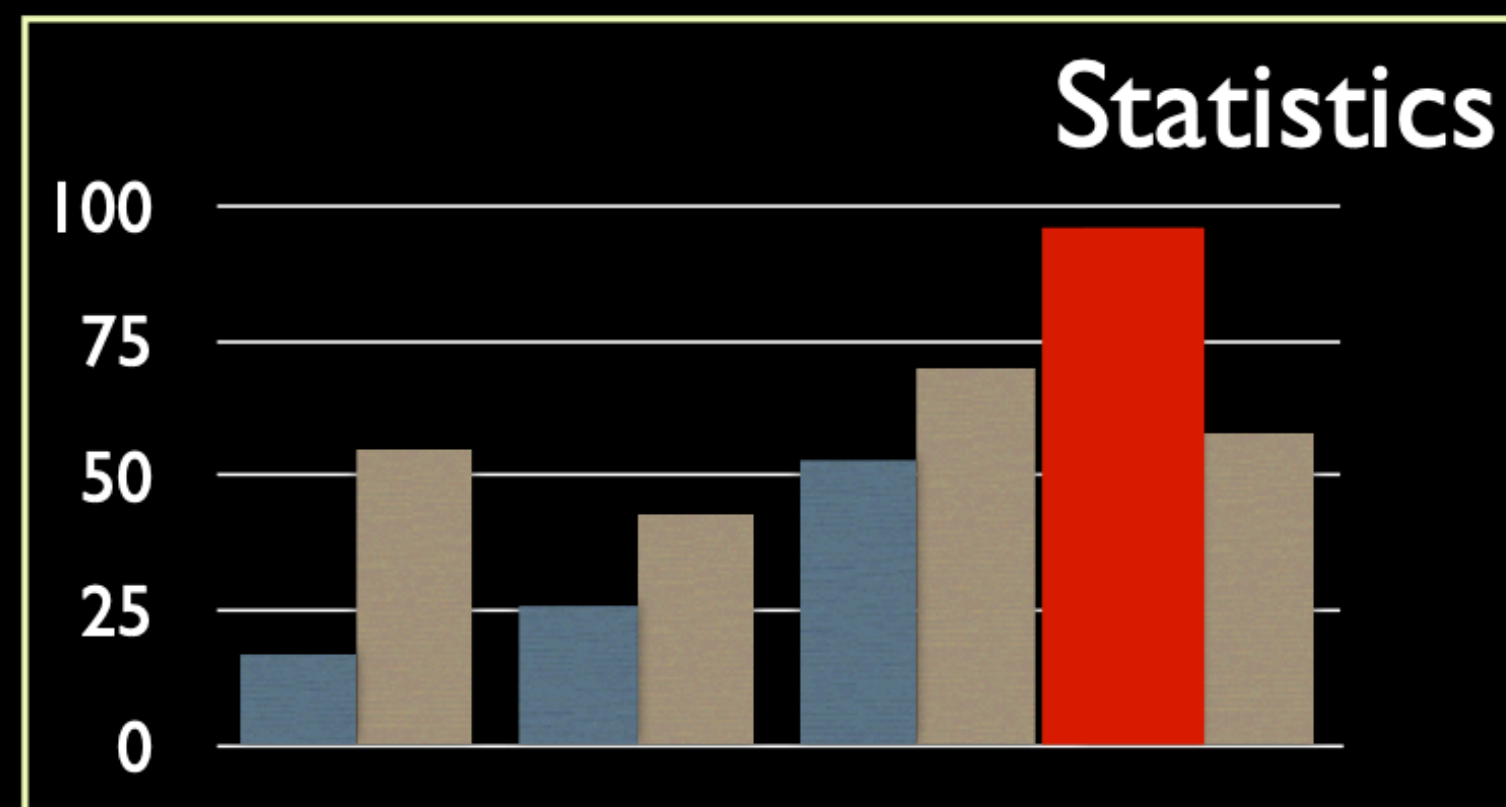
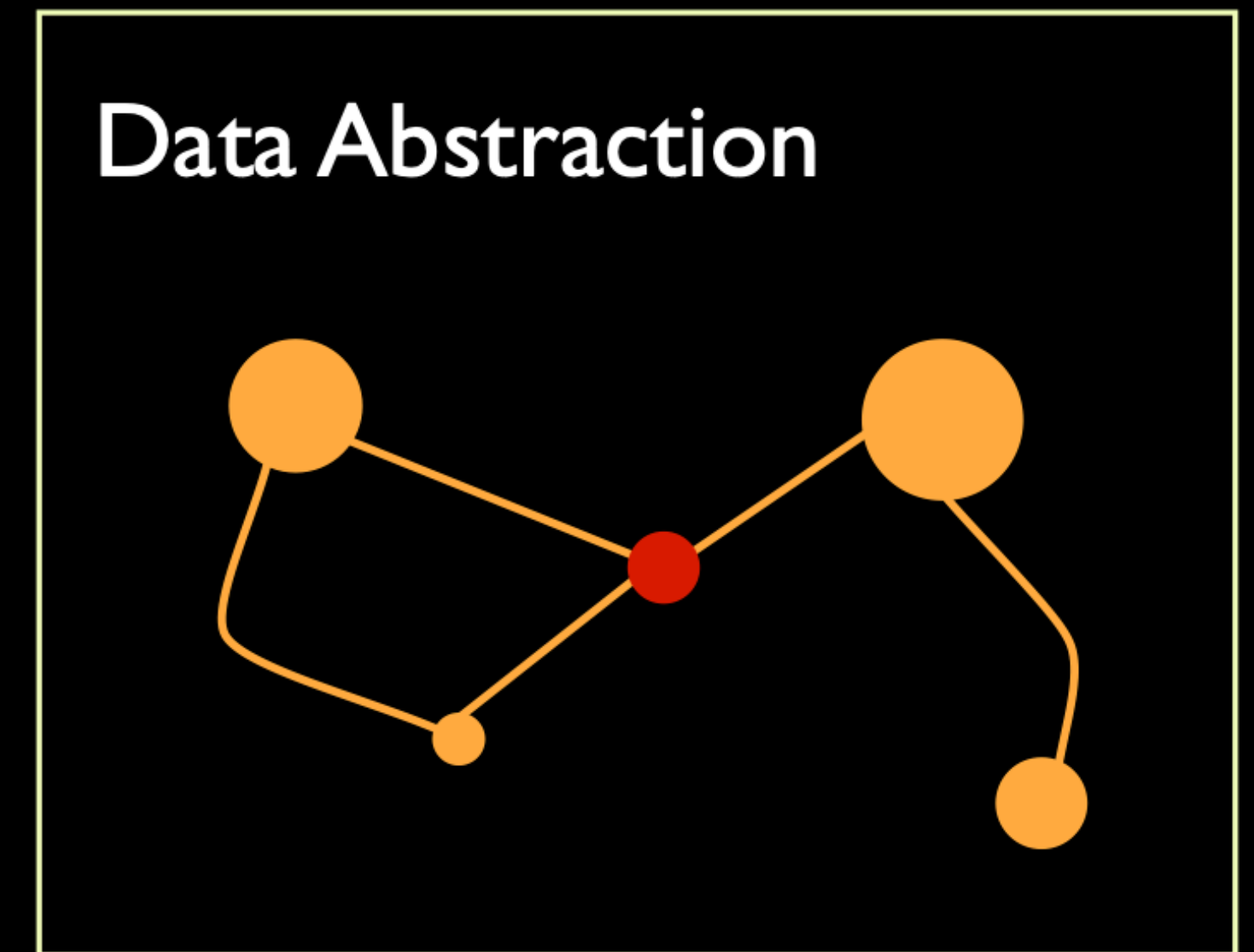
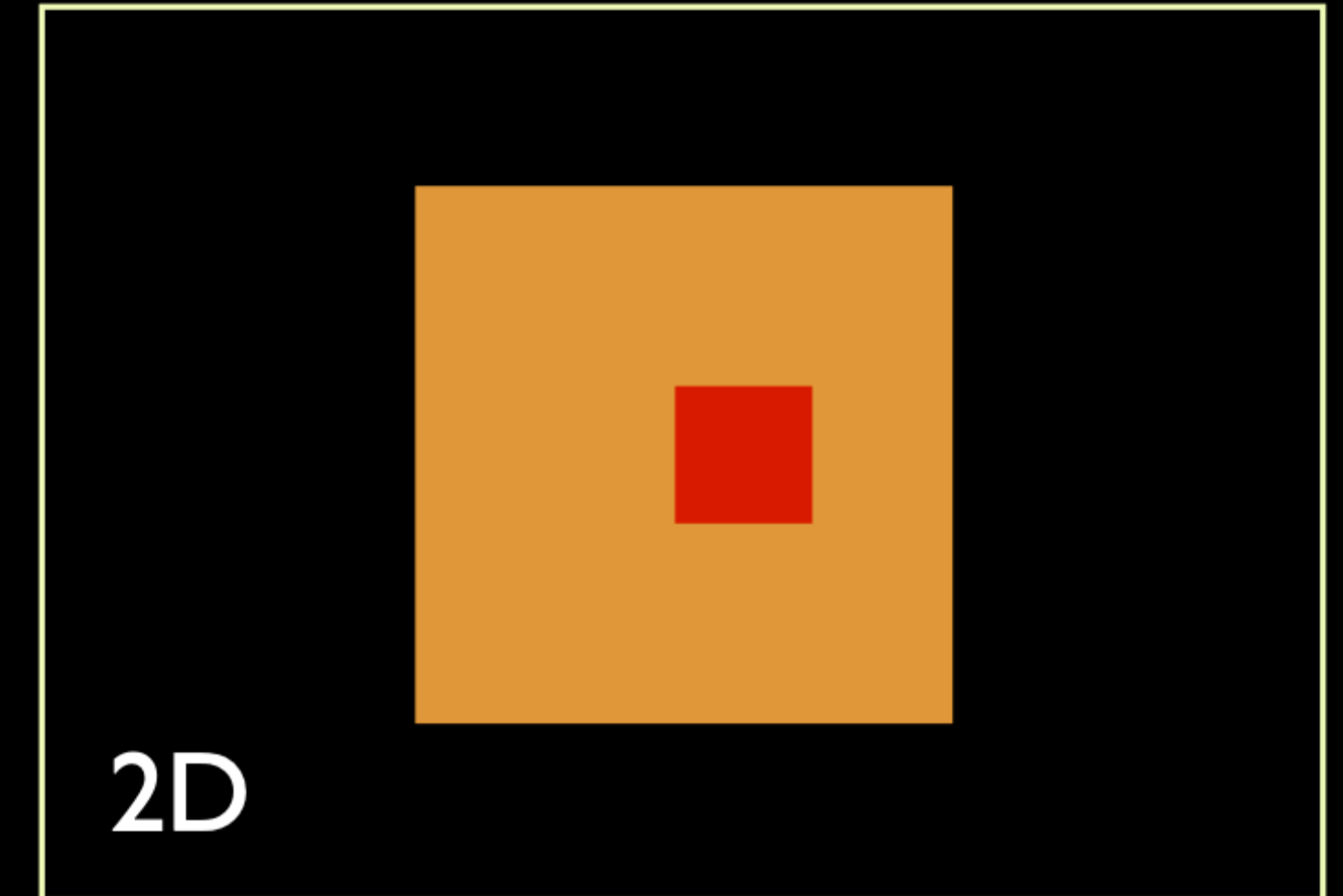
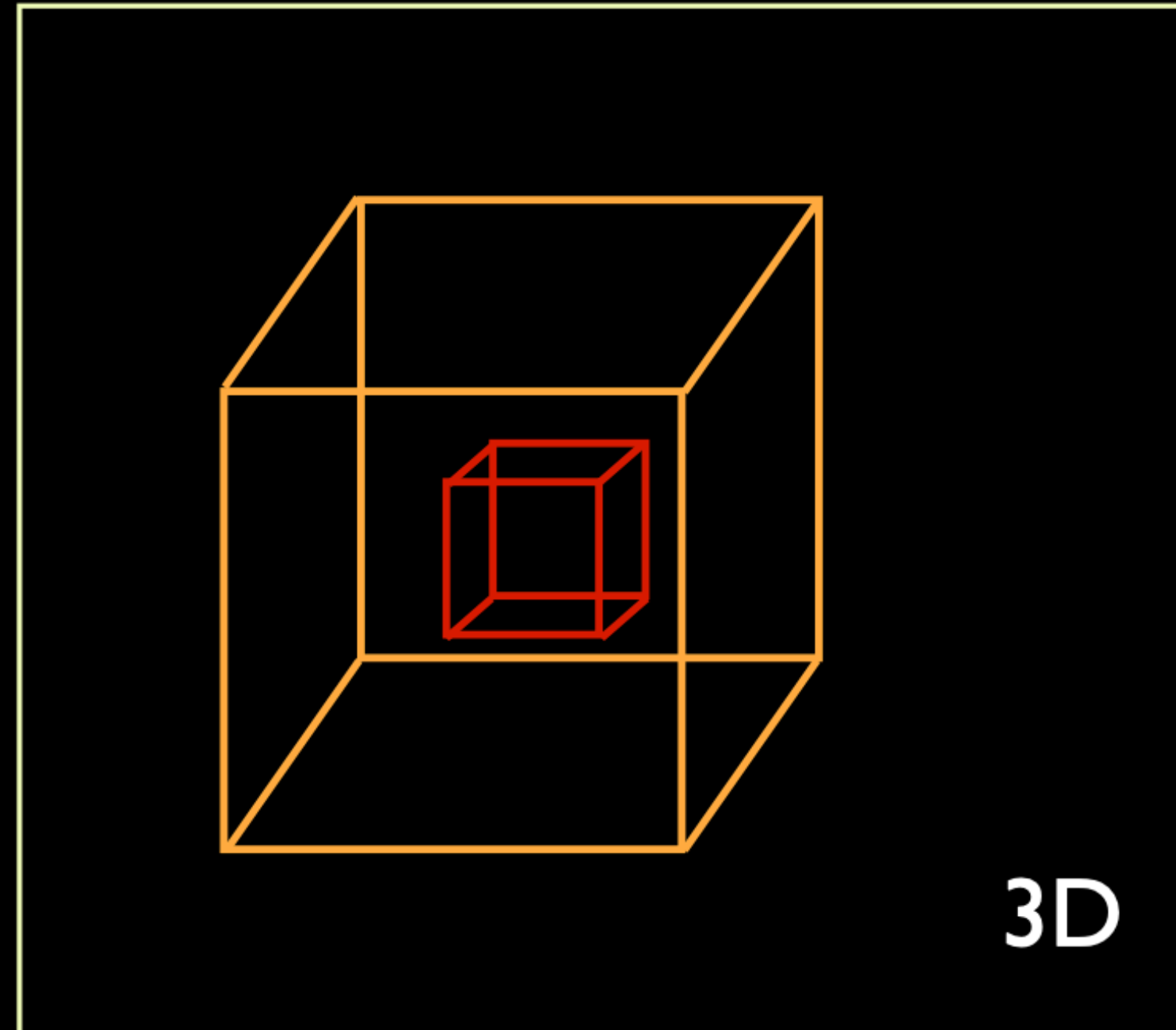


data-set linking

3D selection

infographics

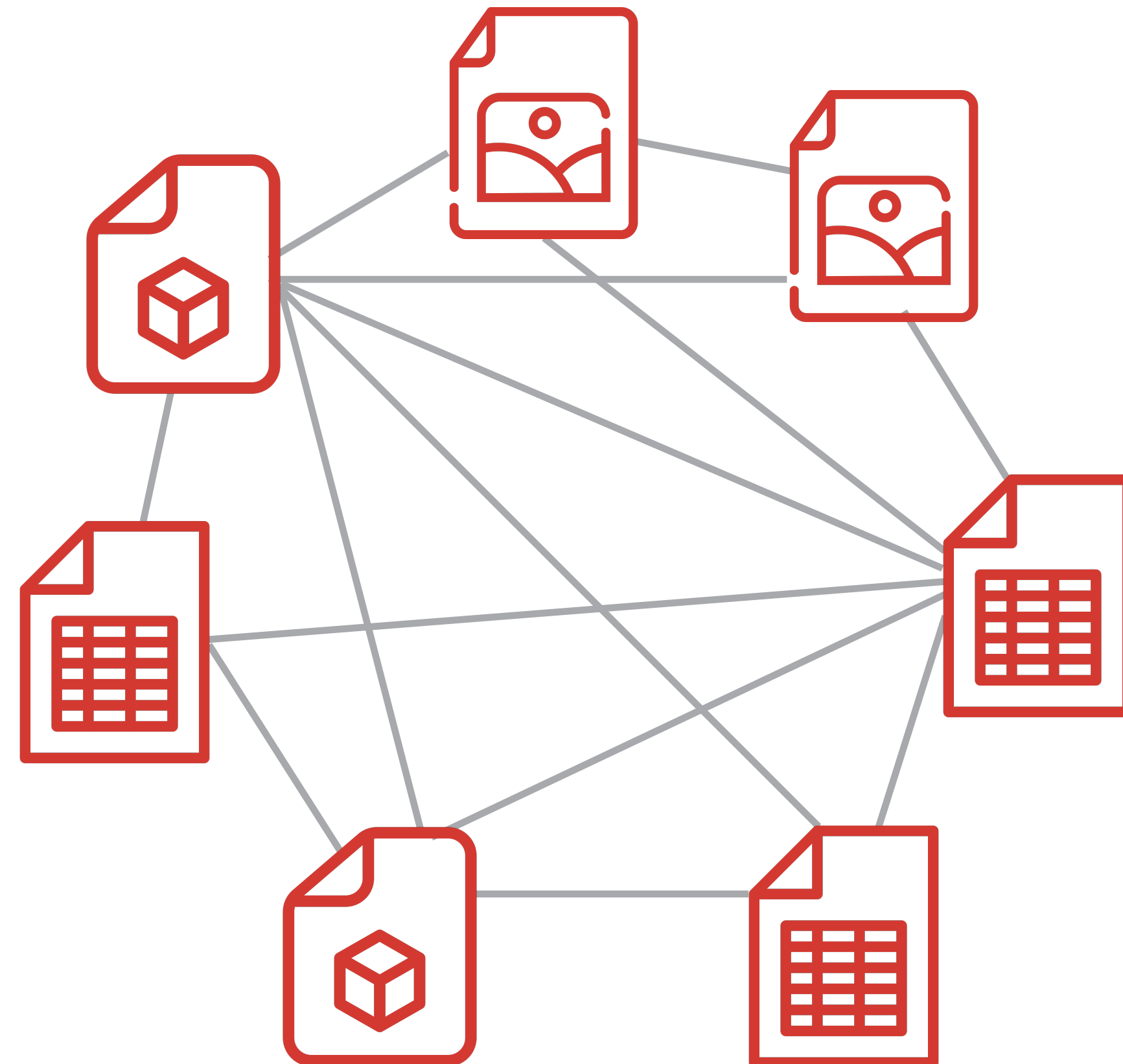
"Linked Views of High-dimensional Data"



What is glue?

multidimensional data exploration

data files' common attributes are **glued**





data files' common attributes are glued



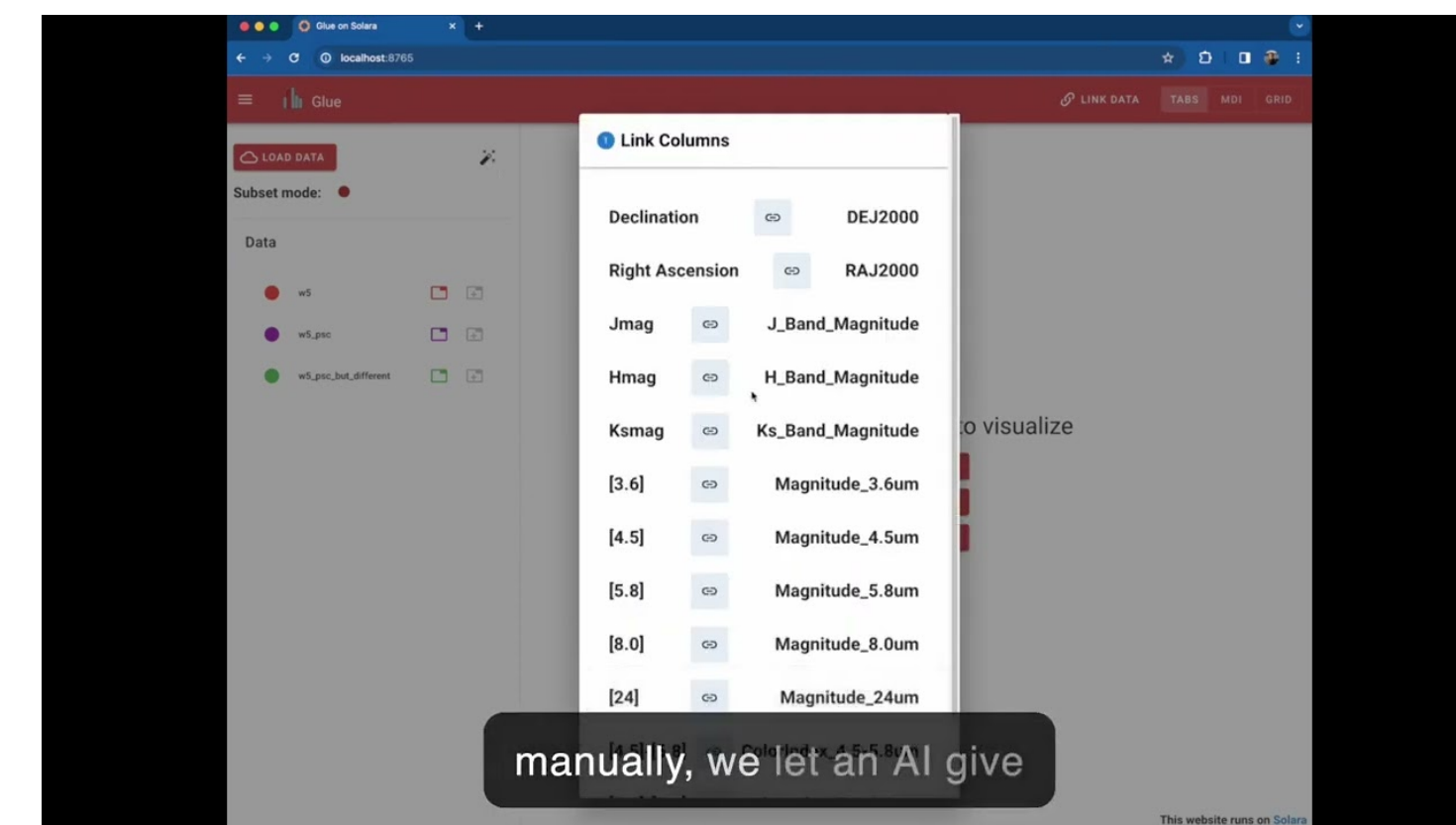
Artificial Intelligence

The ever-expanding capabilities of large-language models and other machine learning techniques can be leveraged to improve LIVE environments. A few areas of focus are identified below, and more are yet to come.

AI-Enhanced Linking Options

Large Language Models (LLMs) can be effectively used to help users automatically create links between diverse datasets with column names that don't conform to specific metadata standards (Zhang et al. 2023, Lobo et al. 2023) . By encoding the variety of columns naming conventions present in a large amount of real world data, LLMs can effectively predict when columns in different datasets refer to the same entity (a form of Entity Resolution), and provide these proposals to the user for acceptance/verification.

We have a short demo showing an **AI-enhanced data linking tool** working in glue-solara. We will post additional updates here so *"watch this space!"*



AI-Enhanced Selection Functions

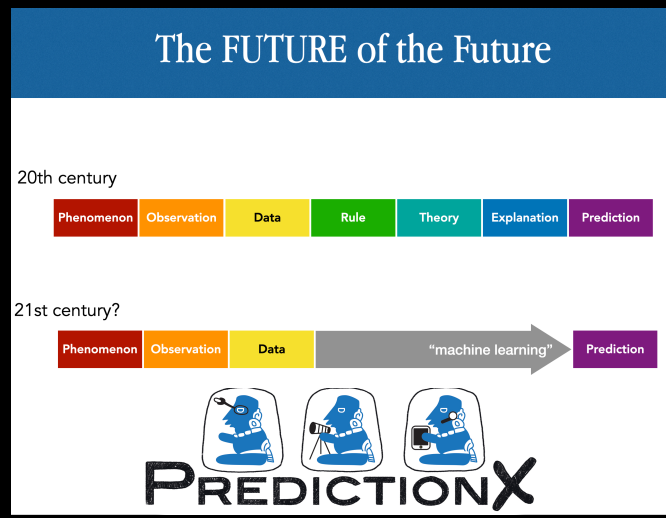
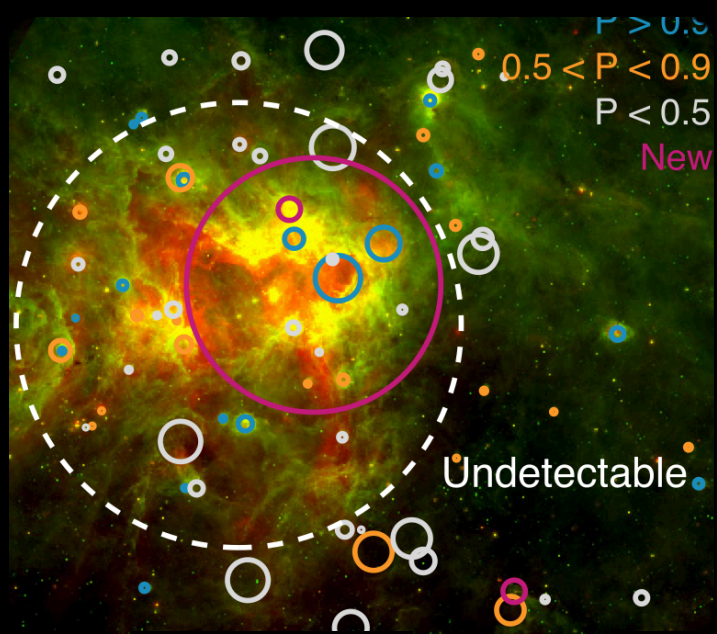
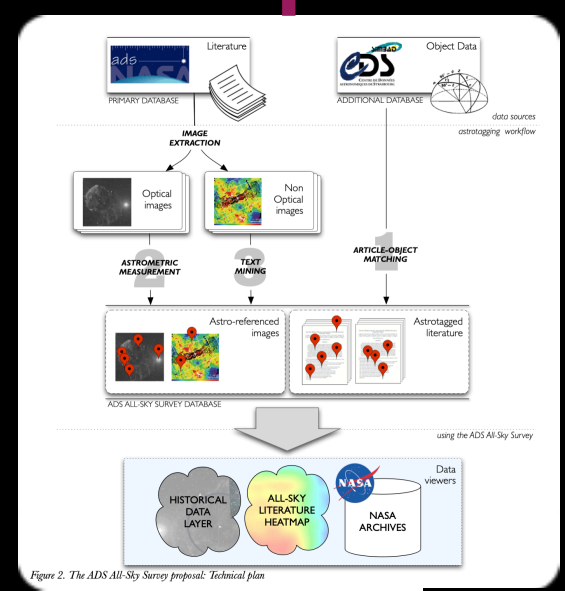
Currently, many of the LIVE tools allow for brushing & linking, as well as algorithmic selection of data subsets, to enable exploratory data analysis. Many recent and ongoing research projects offer clever, often AI-enhanced, tools for selecting data subsets, and it's a near-term goal of the LIVE project to begin incorporating machine intelligence into selection options. While many display types and tables can and will benefit from smart selection, the LIVE team is especially interested in the ~unsolved problem of intelligent 3D selection with volumetric data, so stay-tuned--and do be in touch if you have ideas!



Video courtesy of Maarten Breddels

"Reading Time Machine"

code for visualization

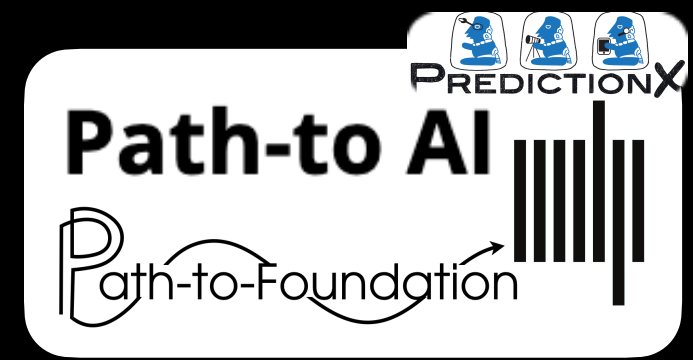


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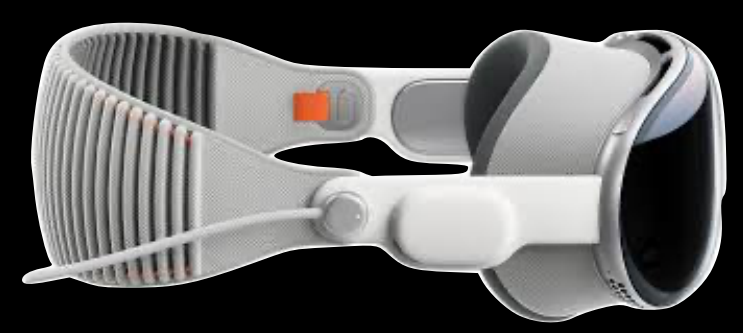
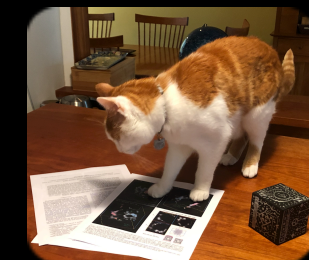
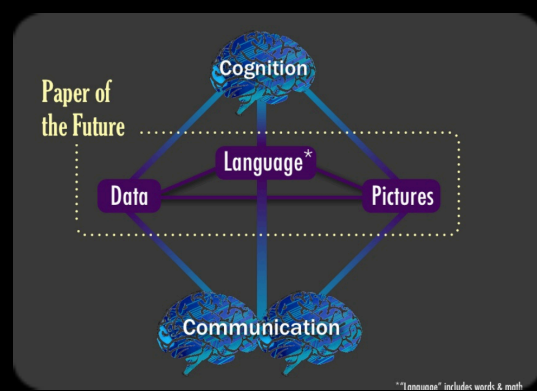
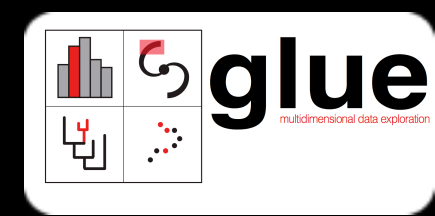
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data-set linking

3D selection

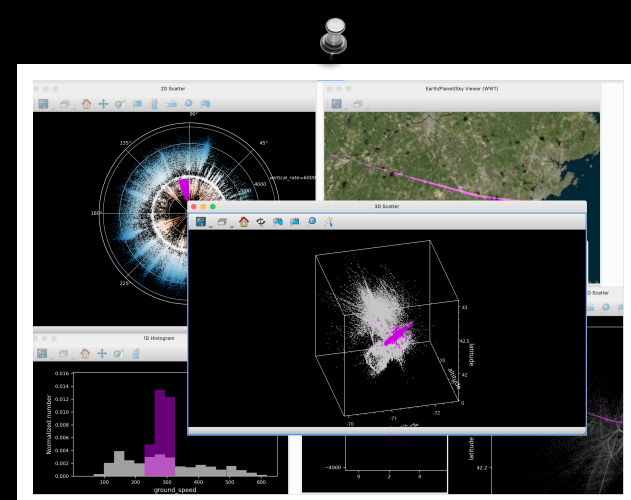
infographics

3D selection

The screenshot displays the Glueviz application window. The main interface is divided into several panels:

- Data Collection:** Shows the loaded data 'planes' and a subset 'Satellite_R_cropped'.
- Plot Layers - 2D Scatter:** The 'planes' layer is selected and set to 'Color' mode with a fixed green color.
- Plot Options - 2D Scatter:** The x-axis is 'vertical_rate', the y-axis is 'altitude', and the plot type is 'rectilinear'.
- 2D Scatter (Left):** A scatter plot of latitude vs. longitude showing a dense cluster of points.
- 2D Scatter (Right):** A scatter plot of altitude vs. vertical_rate showing a vertical distribution of points.
- Earth/Planet/Sky Viewer (WWT):** A satellite map view showing the geographic location of the data points as green lines on a map of the United States.

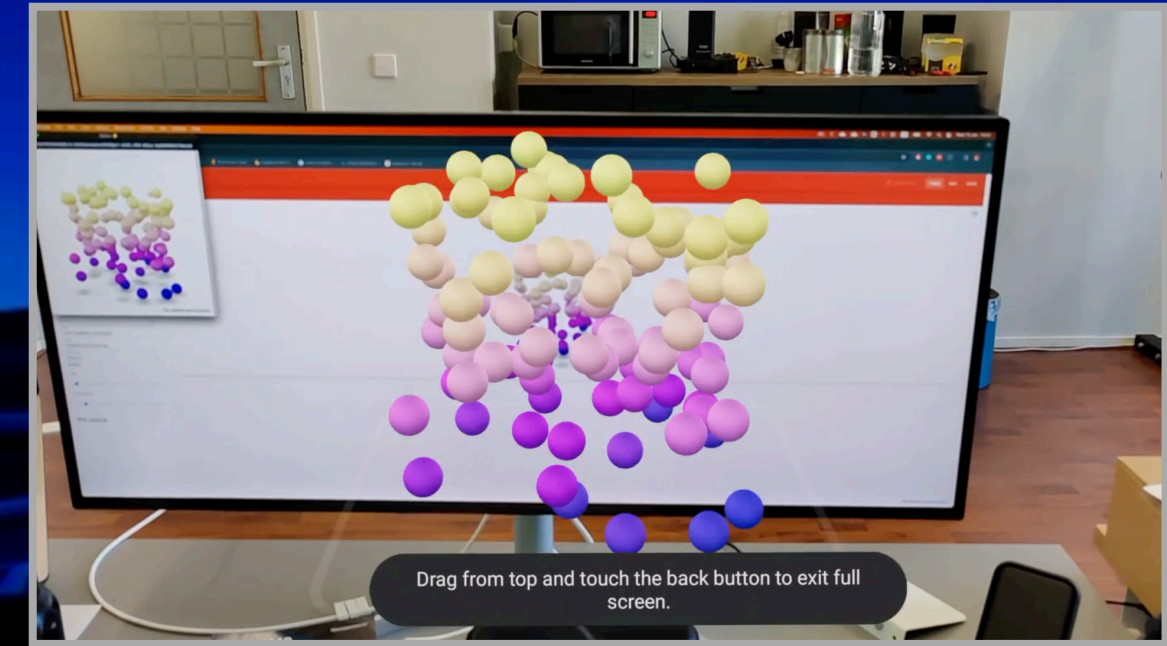
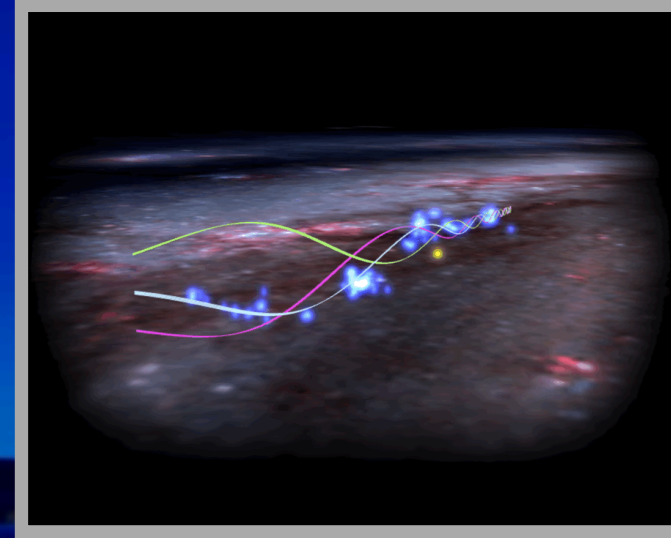
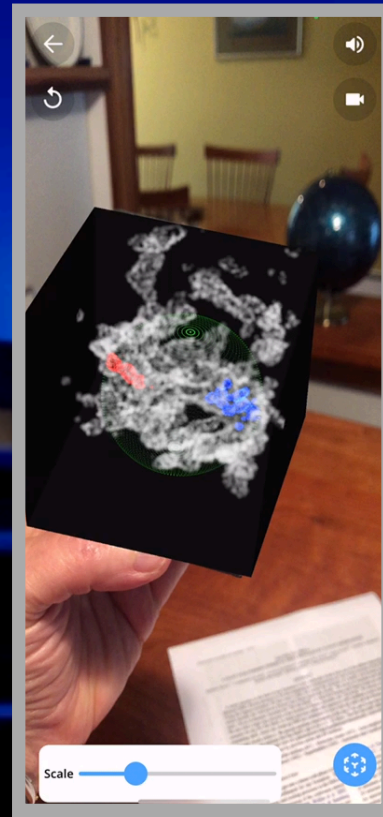
The Glueviz logo is visible at the bottom center of the interface.



ask (later) for LIVE selection demo...

(and "smart" selection more generally!)

3D selection



AR for Science and Outreach

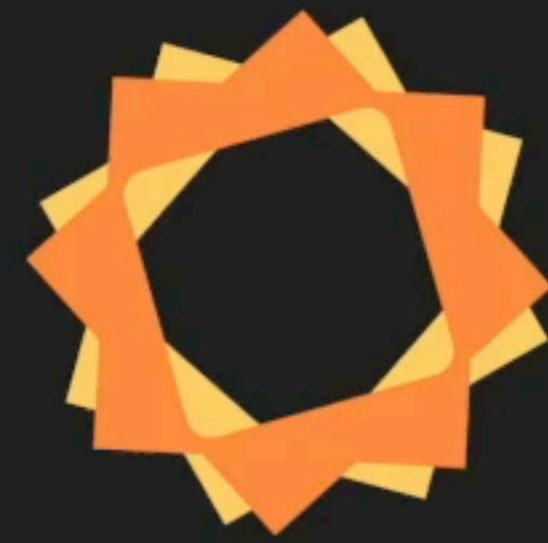
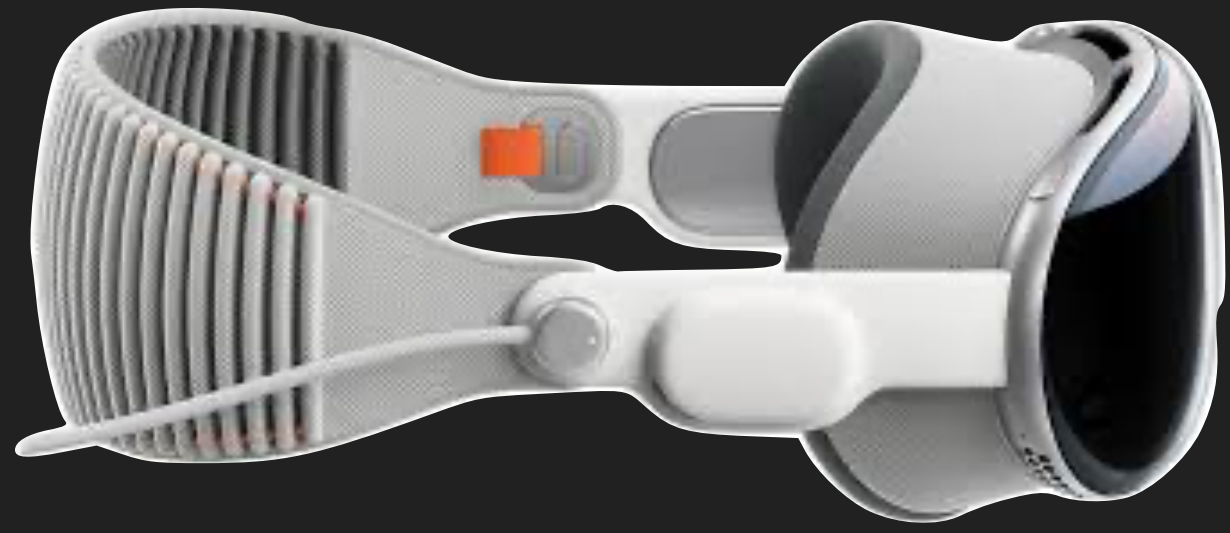
WHAT'S NEXT IN AR?



glueviz.org/glue-ar



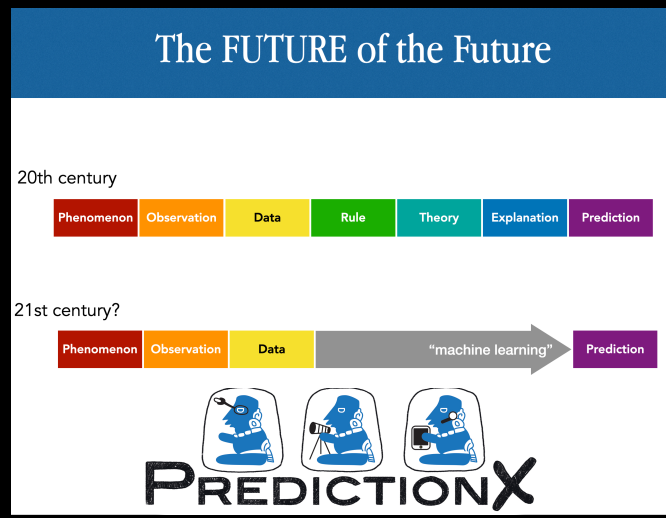
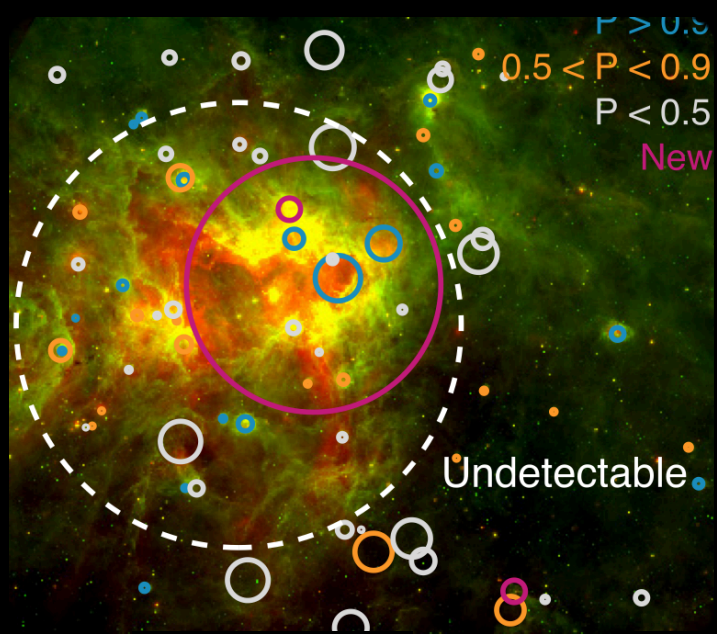
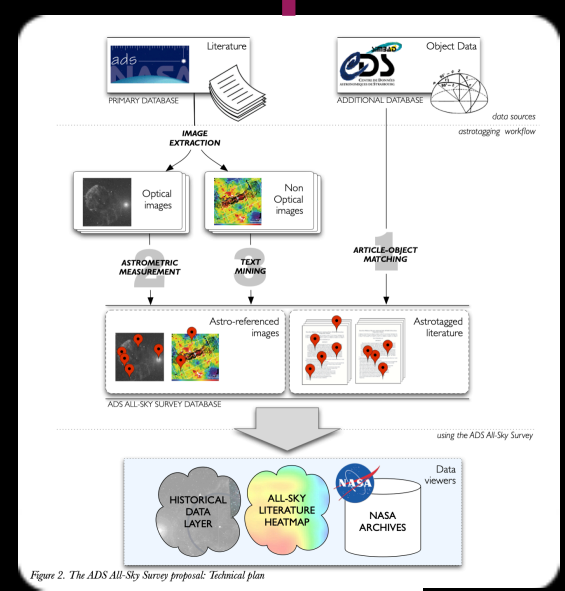
(and "smart" selection more generally!)



SOLARA

"Reading Time Machine"

code for visualization



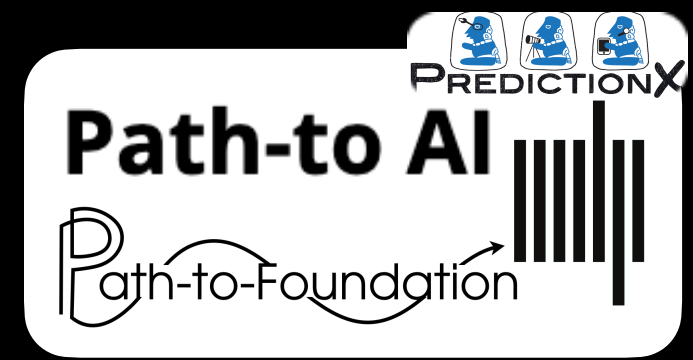
Reading Time Machine

Total % selected (of OCR tokens):

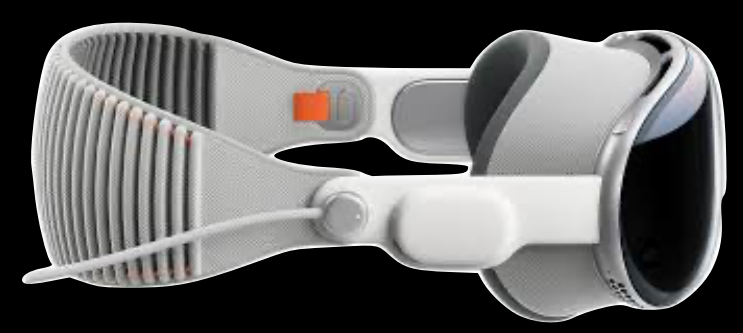
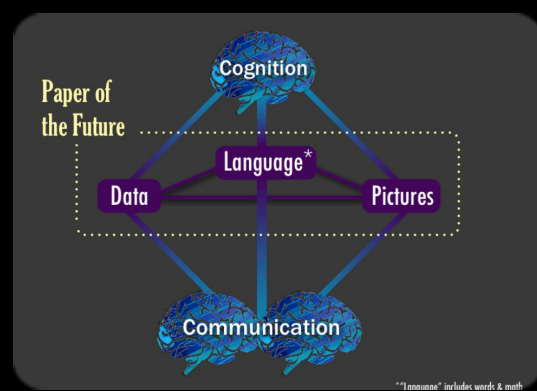
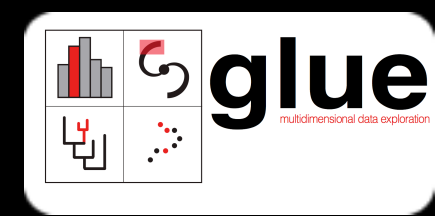
OCR-Ground Truth Dataset

Learn more about the ~200M+ character OCR-ground truth Astronomy literature dataset.

[OCR](#) [LaTeX mining](#) [interactive plots](#)



2012 — 2014 — 2016 — 2018 — 2020 — 2022 — 2023 — 2024 —

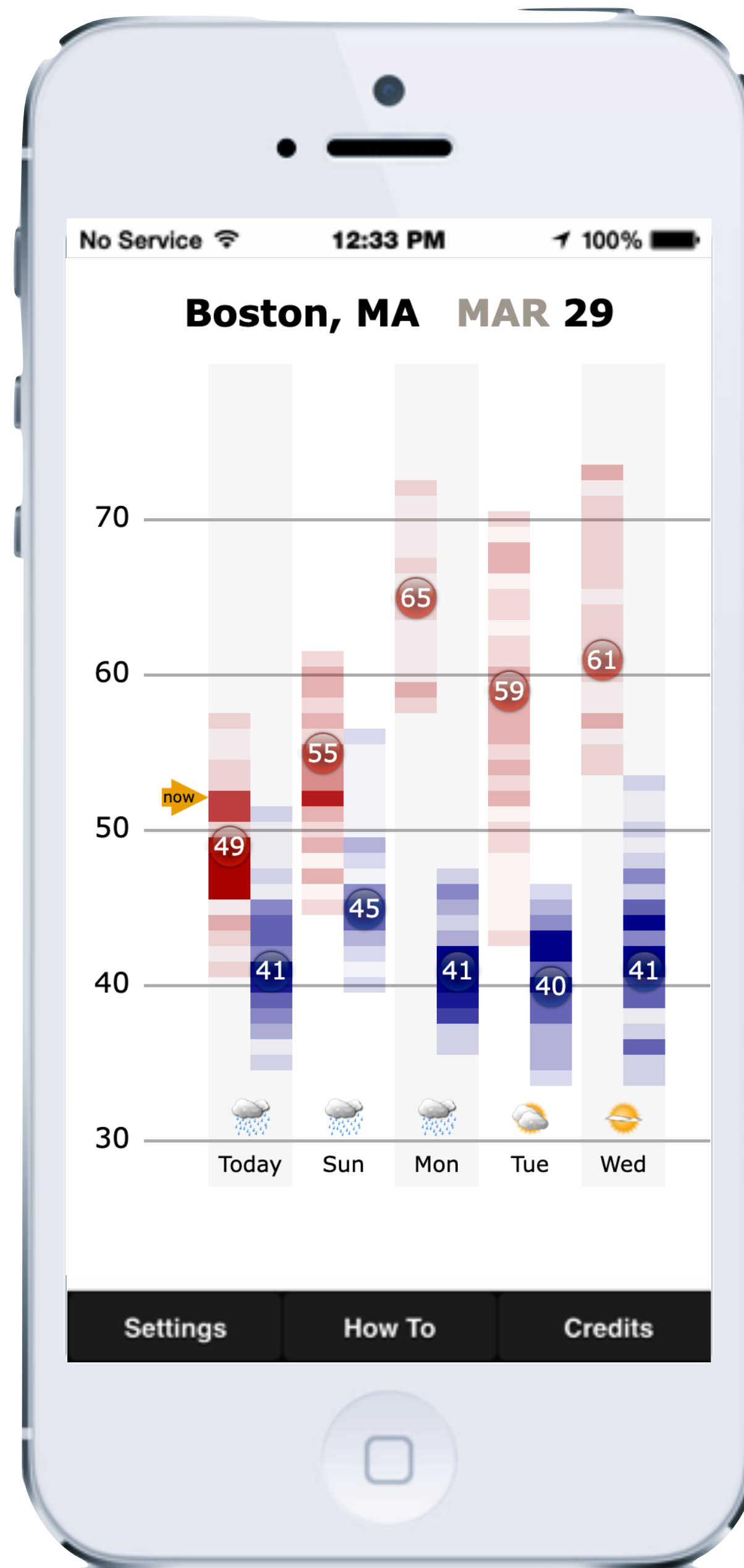


data-set linking

3D selection

infographics

code for visualization



"Take A Sweater"



2011

Take A Sweater
Harvard University

Details Ratings and Reviews Related

iPhone Screenshots

What does this show me?

Settings

Select City: Boston, MA

Date Tolerance (+/- Days): 10

Temperature Tolerance (+/- Days): 5

Show Results

Historical forecast data from ForecastWatch.

Description

NOTE: Take-A-Sweater currently only has data for Boston, MA. This will be changing with the next release.

This App was created in 2012, for use in the Harvard University General Education course "The Art of Numbers," taught by Prof. Ayssa Goodman. The code was written by Bill Barthelmy of Harvard's Academic Technology Group. Historical data were kindly provided by ForecastWatch, a product of Intellovations, LLC. Current five-day weather forecast data are provided by NOAA....

takeasweater.com

with thanks to Eric Floehr of Forecast Watch and Bill Barthelmy of HUIT Academic Technology at FAS





Prediction Journal Visualization

Start Assignment

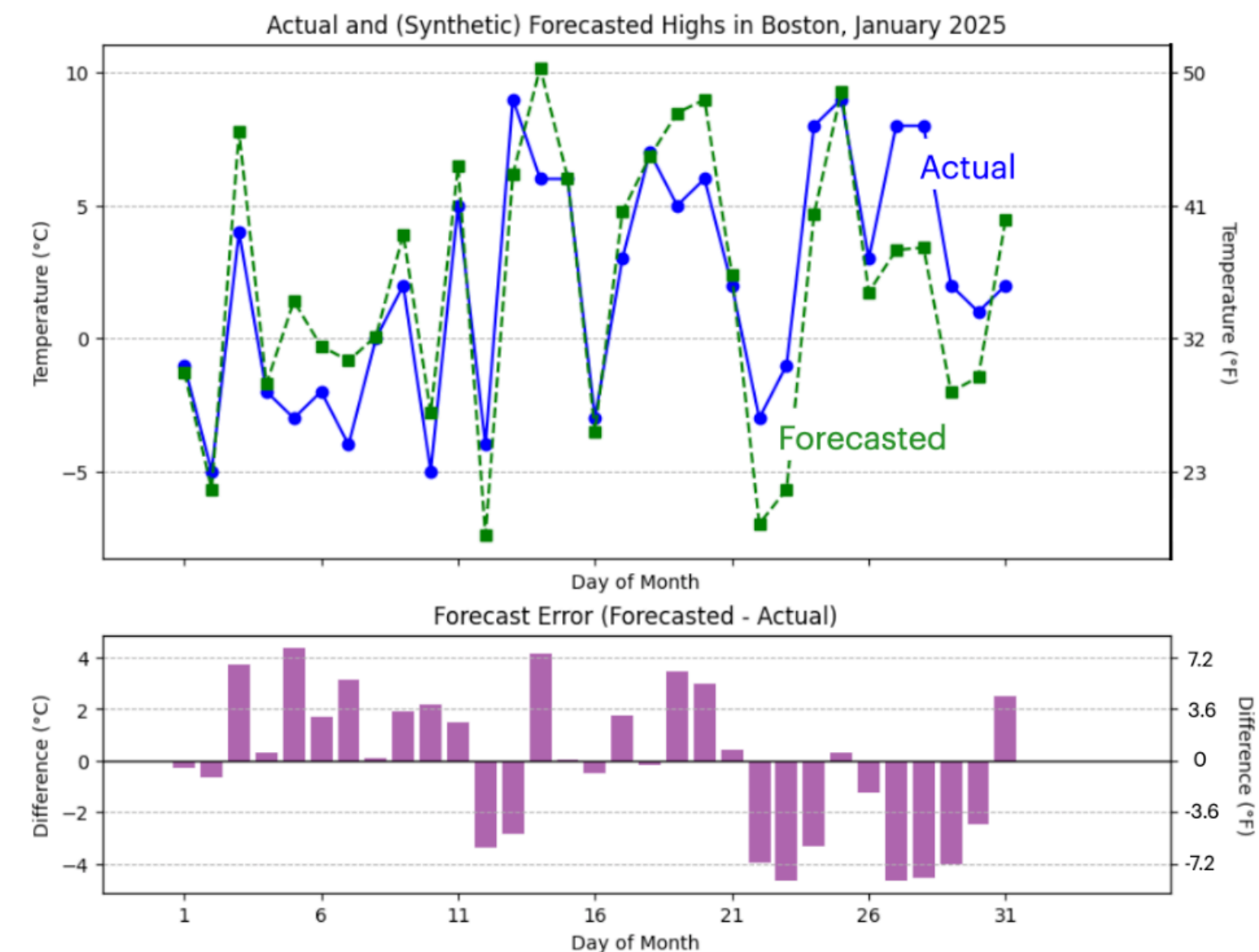
Due Mar 25 by 11:59pm Points 80 Submitting a website url

At this point, you should have 4 weeks worth of predictions and actual outcomes. For this assignment, please:

1) **Create a visualization** of the data you've collected (these will likely include, at the very least, your predictions, recorded outcomes, and dates/times). Visualizations can take many forms and **will depend on your predictions and the type of data you collected**. Talk to your TF for ideas and/or help! Feel free to use computer programs or complete visualizations by hand (see example below or [explore more options here--and remember, yours need NOT be super-fancy, just informative--hand-plotting is fine](#)) .

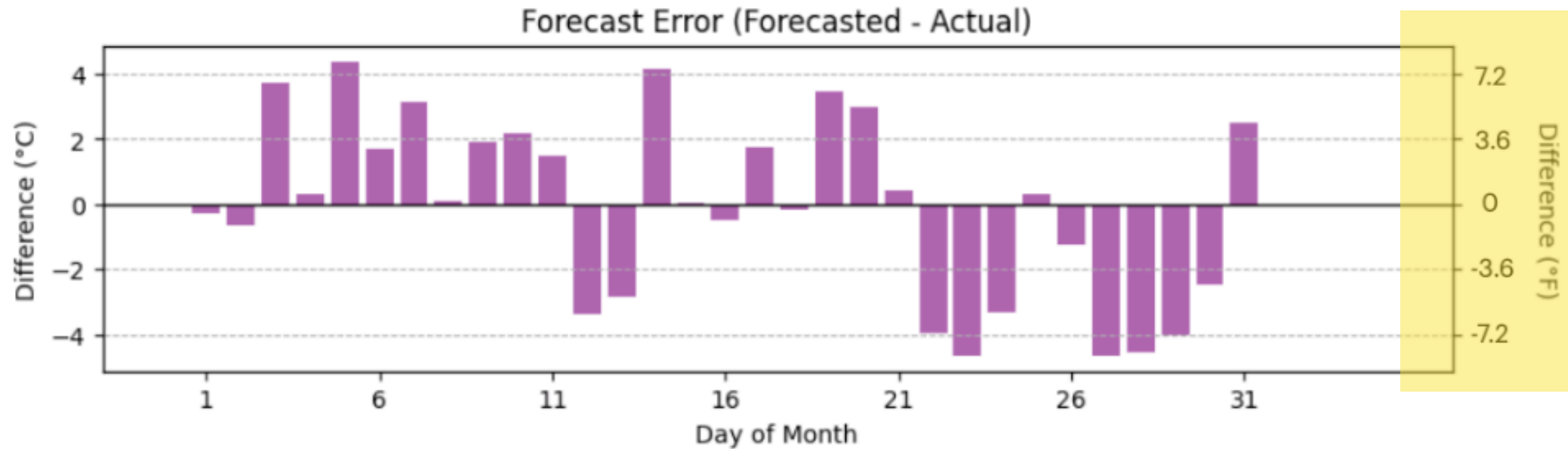
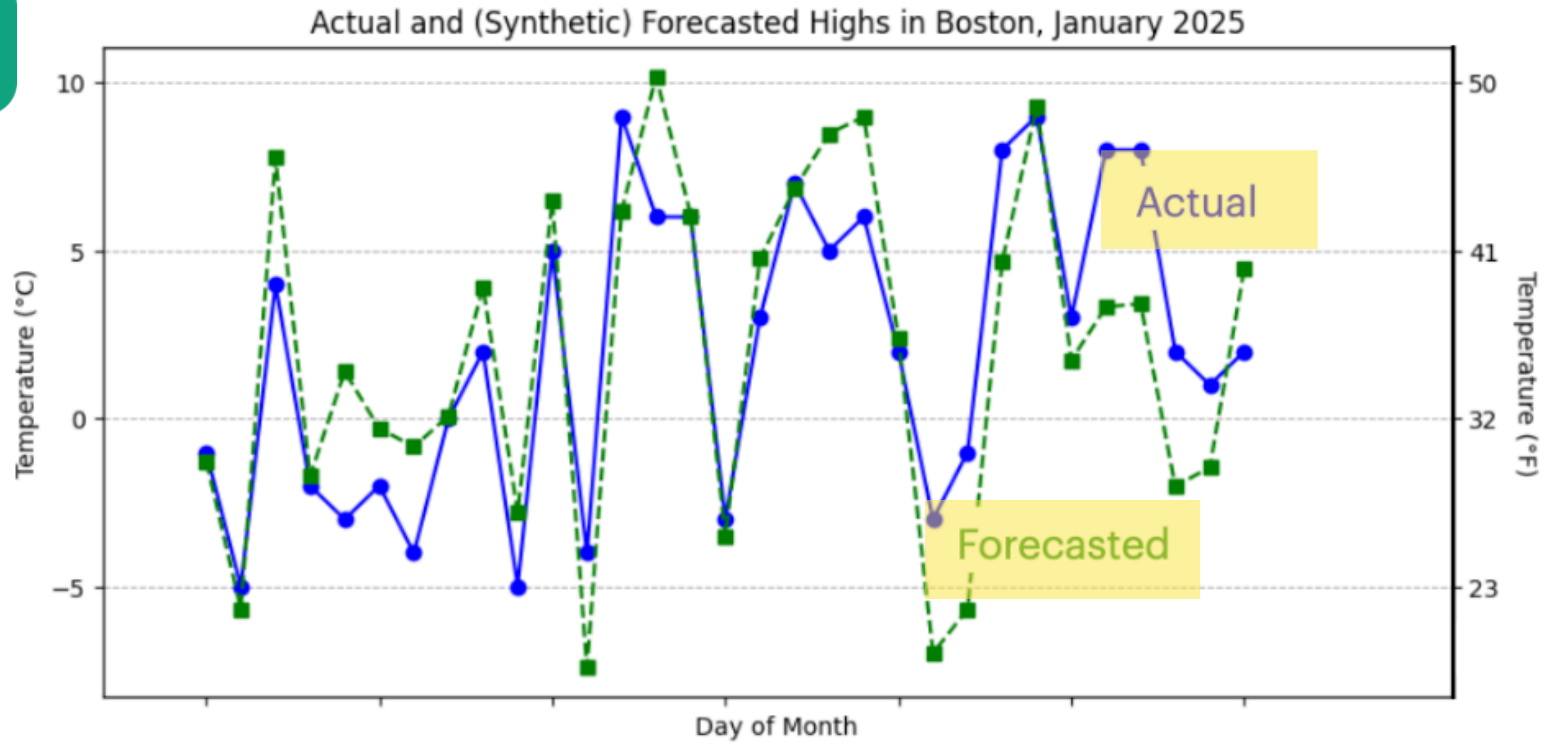
2) **Reflect on your prediction process over the past 4 weeks** using your visualization and the [Padua Rainbow](#) . How have your predictions changed in the past weeks? What parts of the Padua Rainbow have you engaged, what parts have you not engaged, and why? What story does your visualization tell about your own predictive process? Your reflection should be ~500 words.

code for visualization





code for visualization



manual adjustments!



6 days later...

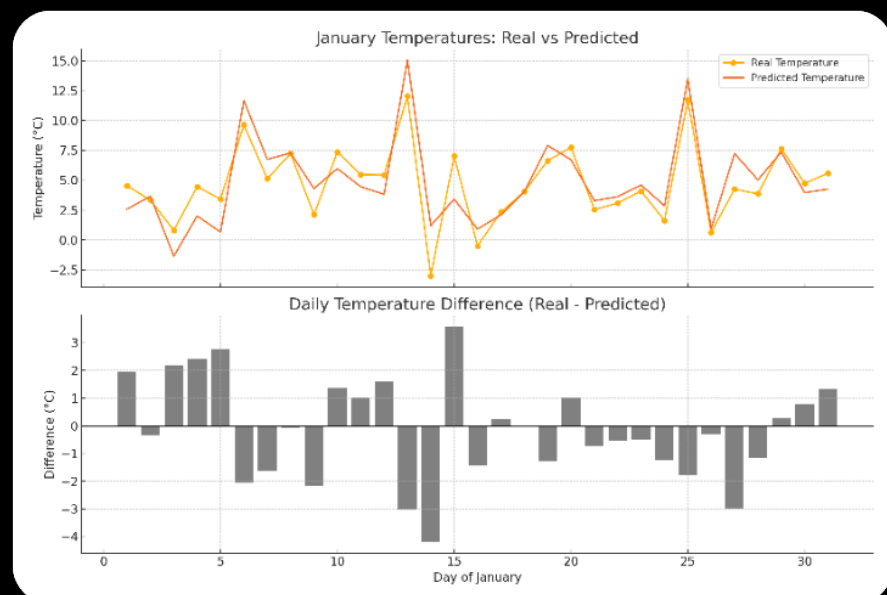


Create an image that contains two graphs - one a line graph that shows the month of January in days on the X axis, with the y axis as the temperature. There should be two lines - one showing the real temperature, and the other showing a predicted forecast, so that the difference can be compared. The second graph should quantify that difference for each day - e.g. if one day was 2 degrees warmer than expected, the lower graph would show +2 for that day.

Here are the two graphs:

- The top graph shows the real vs. predicted temperatures for each day in January.
- The bottom graph visualizes the daily difference between real and predicted temperatures (real minus predicted), making it easy to spot where predictions were too warm or too cold.

Let me know if you want to adjust the style, range, or add real data. [?](#)



March 31, 2025

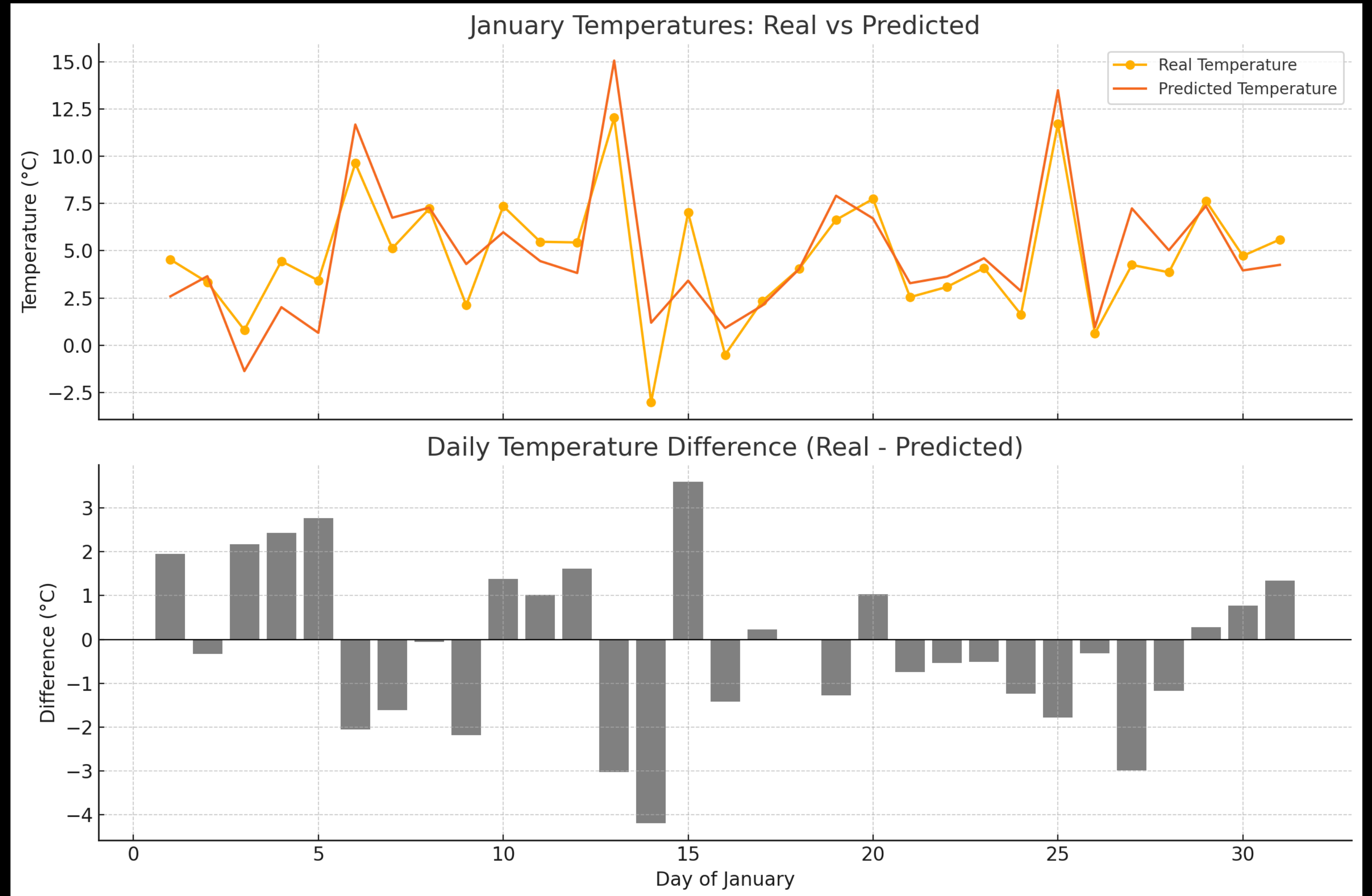
No python, single prompt generation. Holy smokes that's a huge leap of improvement

11:18

Sim Sayer

Remarkably, the graphs appear to correspond

code for visualization



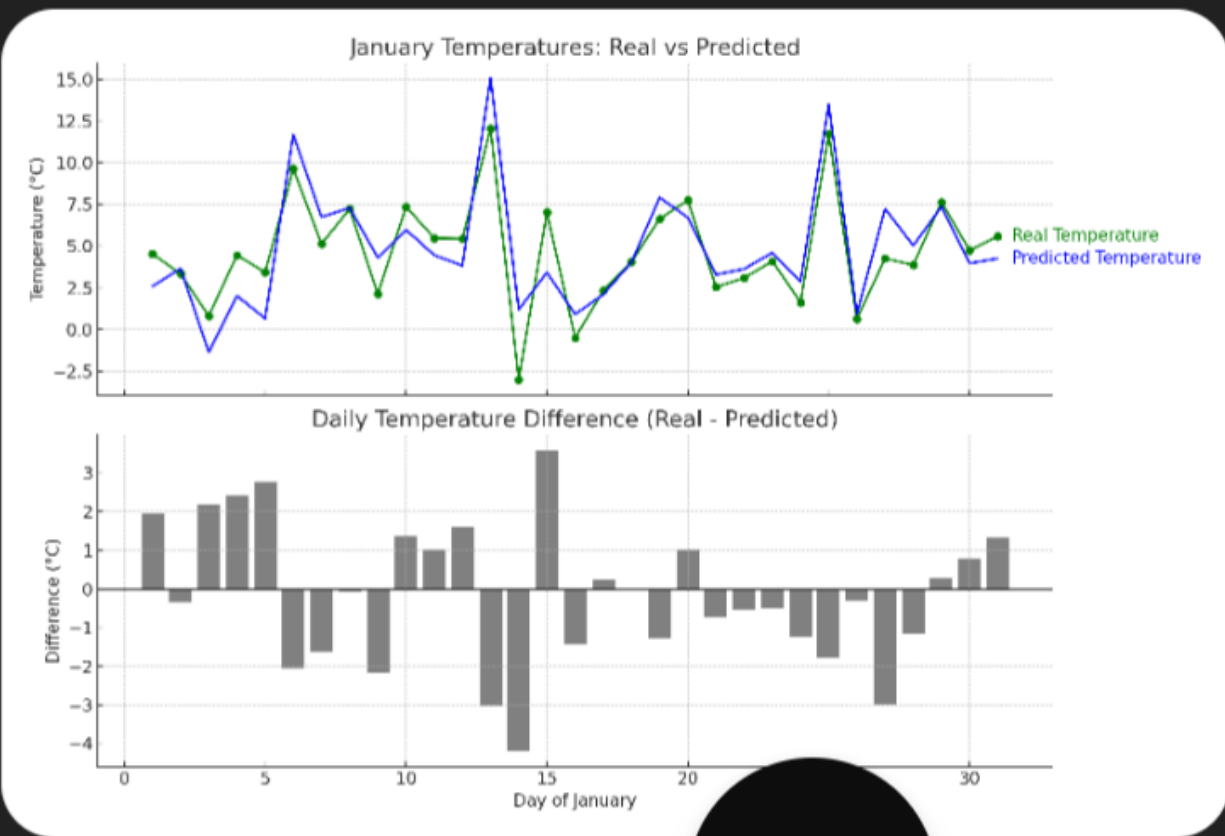


Now instead of a legend, have the text appear near the line instead. And make the real line green and the predicted line blue. Use the same data to build the graph

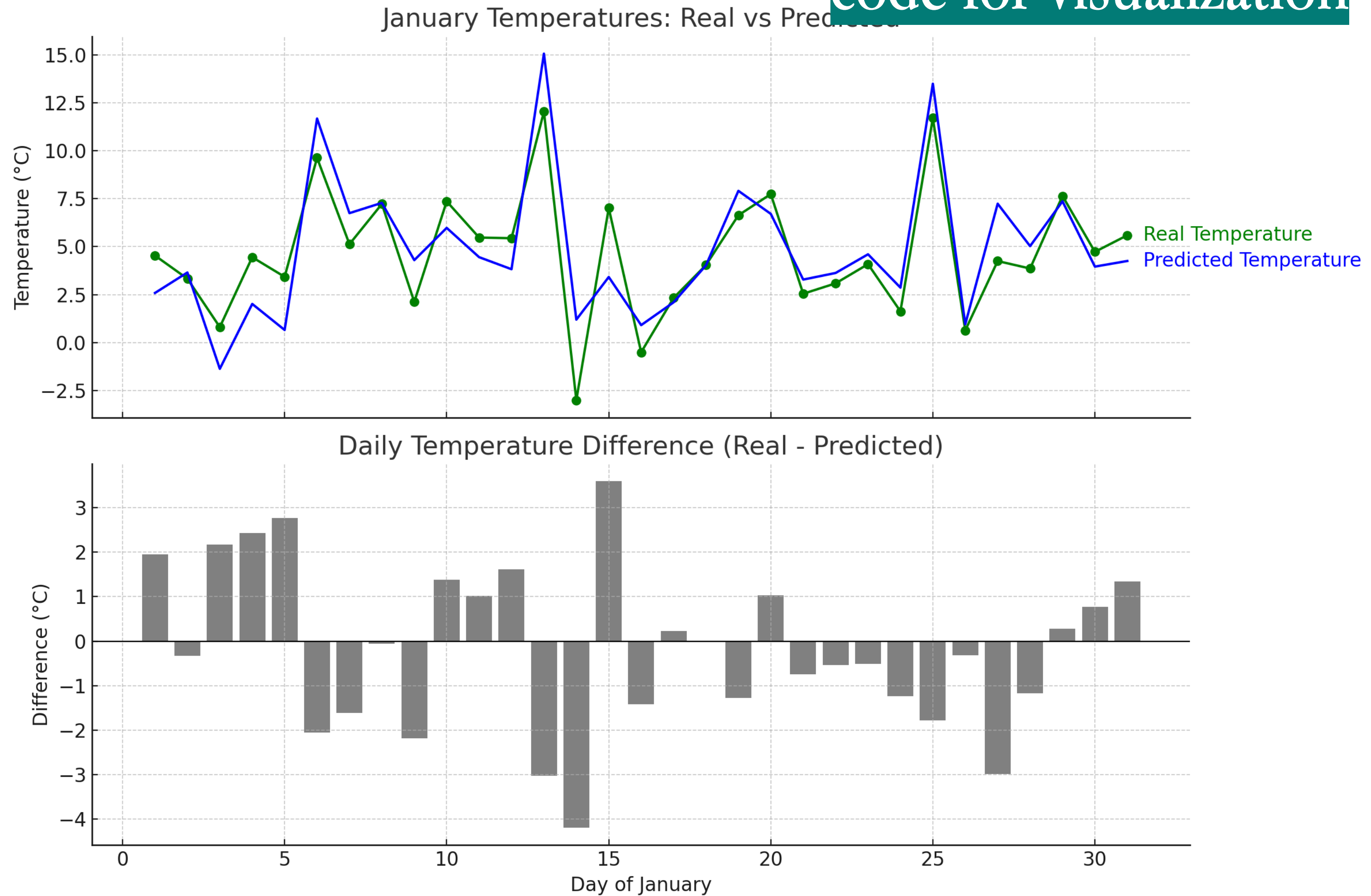
Here's the updated version of the graphs:

- The top graph now uses **green** for the real temperature line and **blue** for the predicted temperature.
- Instead of a legend, the labels appear directly next to the respective lines.

Let me know if you'd like to adjust the font size, move the labels, or apply any other styling. ①



code for visualization



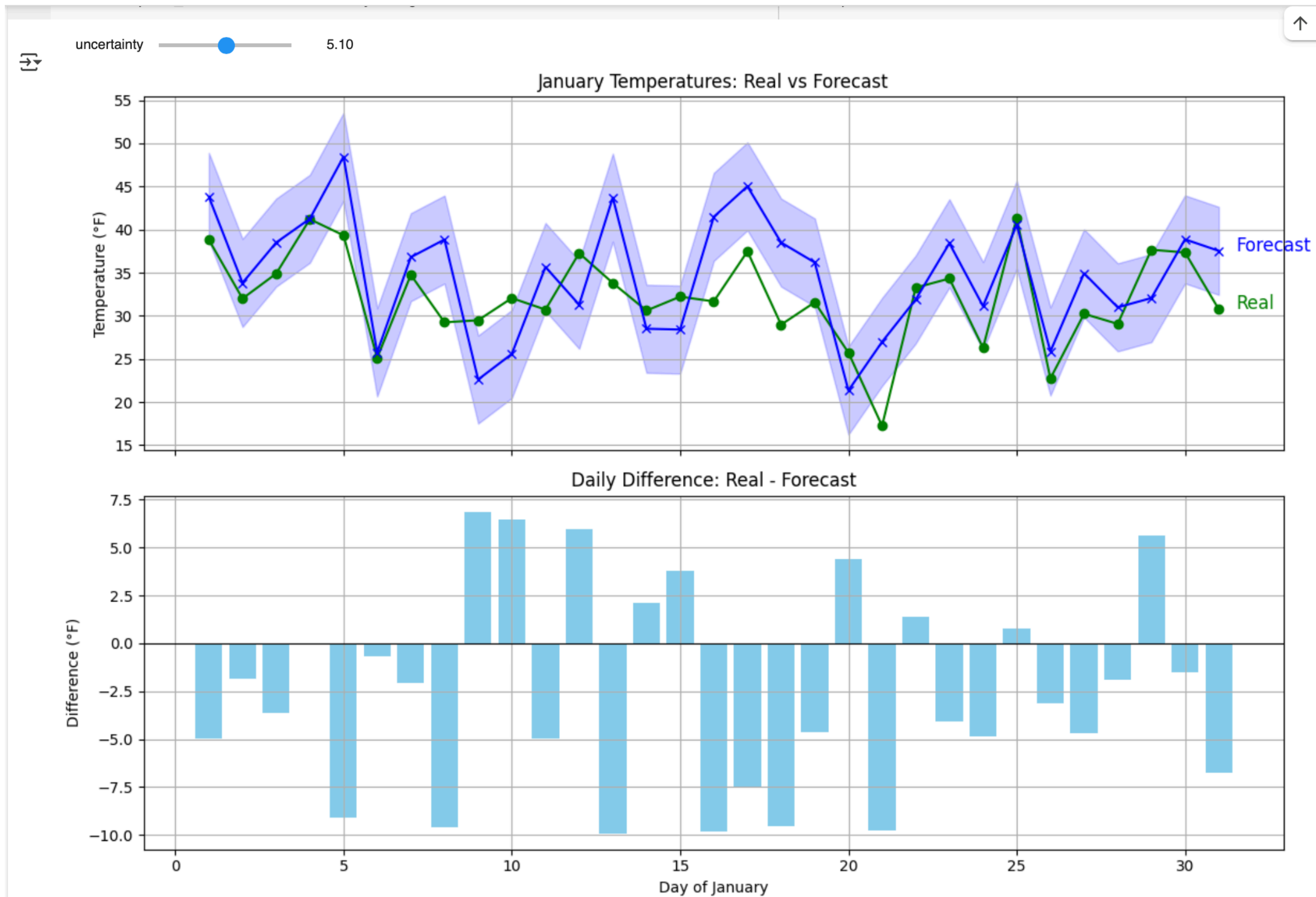
April 4, five days later: let's add a slider, and get *fancy*... [DEMO, ChatGPT, Jupyter, Colab]



Temperature_Forecast.ipynb ☆ 🌐
File Edit Insert Runtime Tools Help
Code + Text



code for visualization



```
plot_forecast
def plot_forecast(uncertainty)
<no docstring>
```

ChatGPT 4o >

OK, that's great--can we try a fancier visualization now?

Absolutely, let's level it up! 💡

What kind of *fancy* are you thinking?

Here are a few ideas to get us started:

🌟 Fancy Visualization Upgrades

1. Interactive Plotly Dashboard

- Use [Plotly](#) for beautiful, zoomable, responsive charts
- Sliders, dropdowns, hover tooltips, and uncertainty bands
- Works great in Colab too!

2. 3D Surface or Heatmap

- Show temperature trends across multiple months or locations
- Useful for visualizing patterns a 3D Forecast Temperature Explorer

3. Animated Forecast Evolution

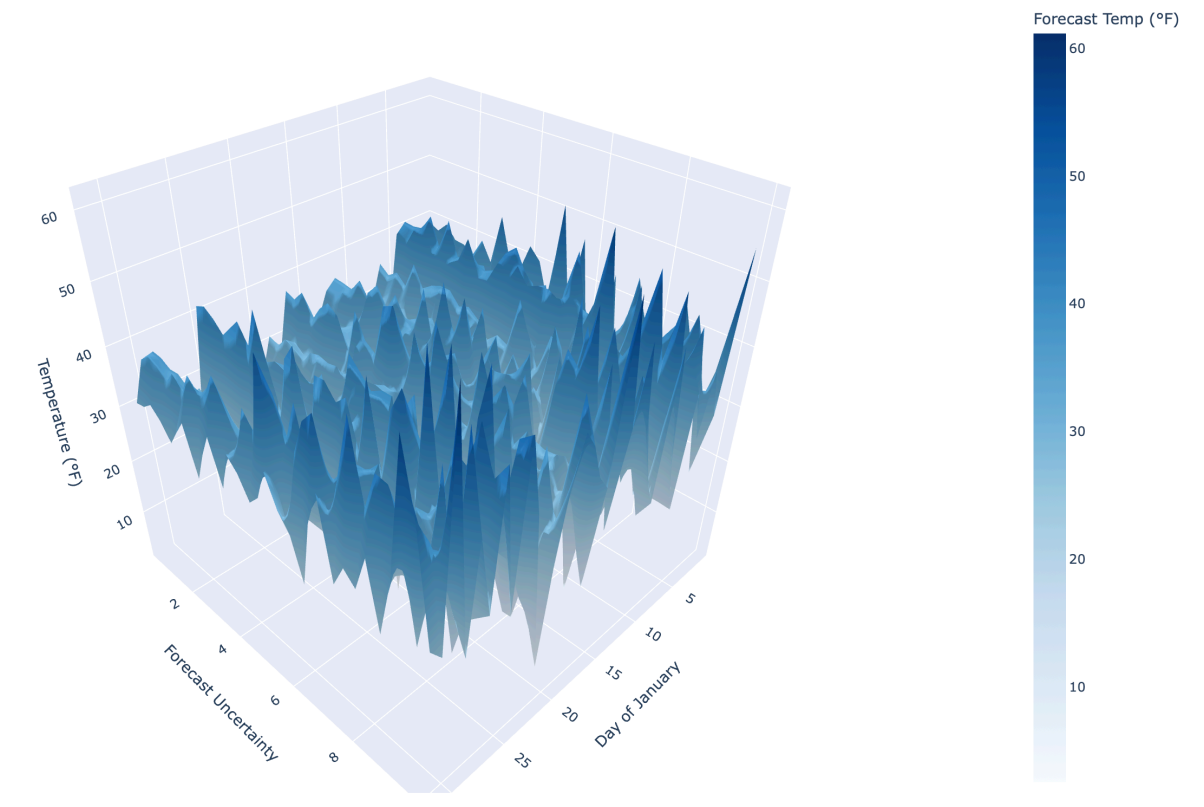
- Animate how the forecast changes over time
- Could be a `matplotlib.animation`

4. AR-Ready or Globe Visualization

- For geographic data: World or globe

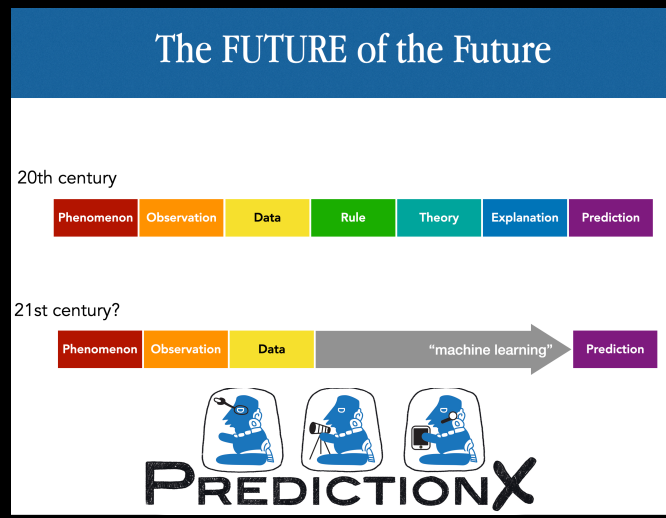
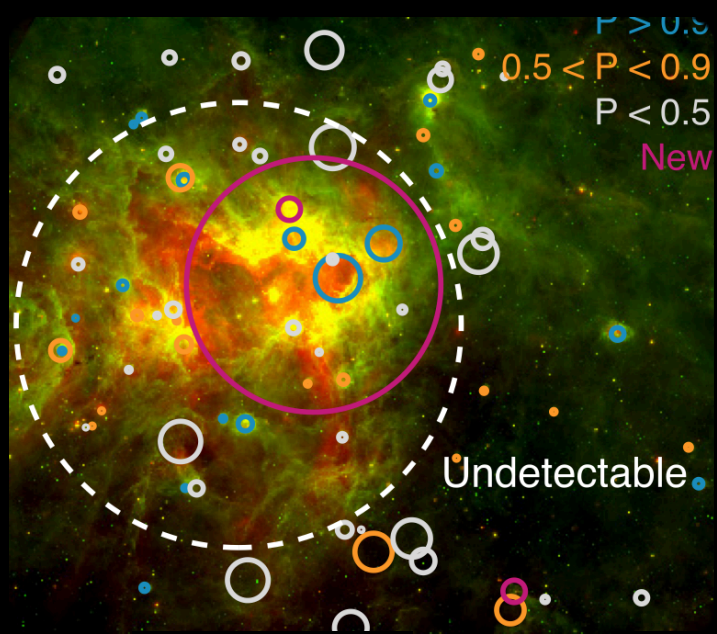
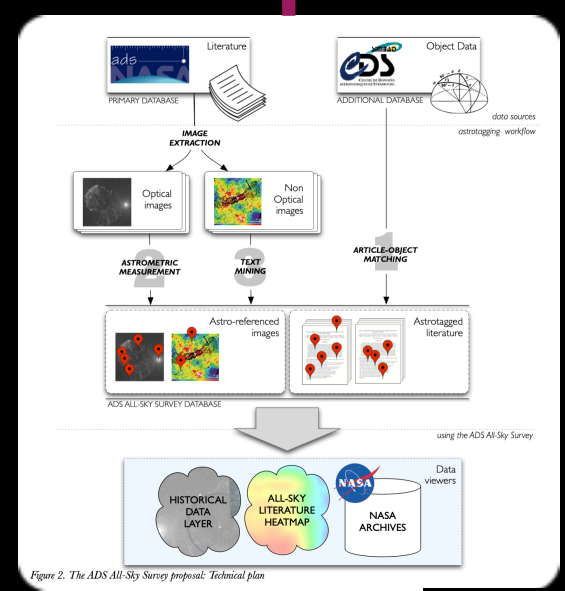
5. Time Series Decomposition (Forecast)

- Show forecast vs. trend, seasonality, and noise
- Use `statsmodels` or `Prophet`



"Reading Time Machine"

code for visualization

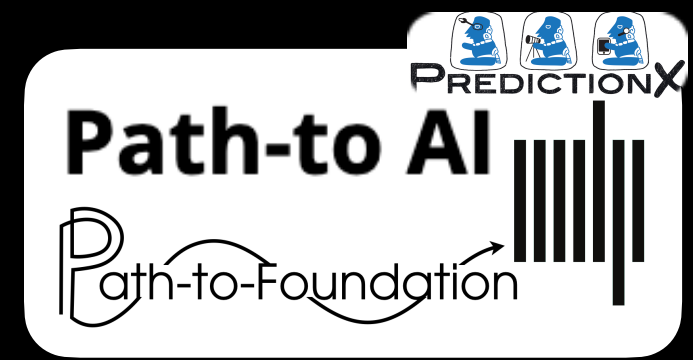


Reading Time Machine

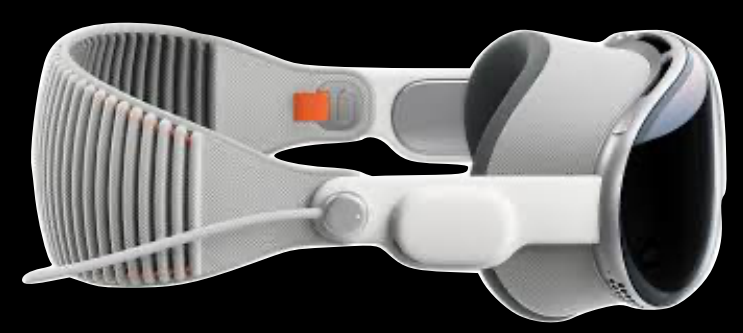
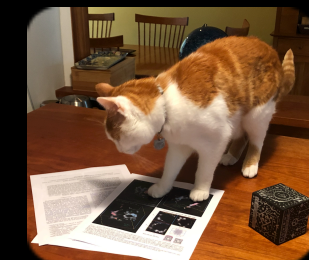
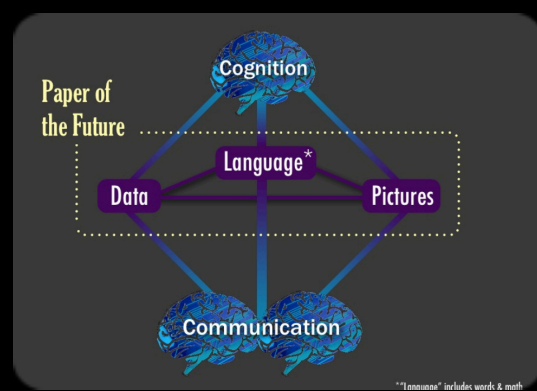
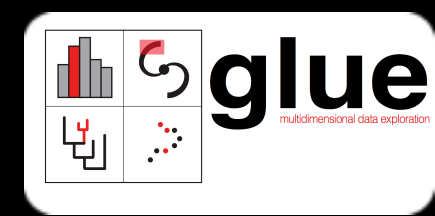
Total % selected (of OCR tokens)

OCR-Ground Truth Dataset
Learn more about the ~200M+ character OCR-ground truth Astronomy literature dataset.

[OCR](#) [LaTeX mining](#) [interactive plots](#)



2012 — 2014 — 2016 — 2018 — 2020 — 2022 — 2023 — 2024 —



data-set linking

3D selection

infographics



AI in my Astro+Visualization Life Today*

Alyssa Goodman, Center for Astrophysics | Harvard & Smithsonian

*April 2025

AI in my Astro + Visualization Life Today

I have been lucky enough in my career so far to watch, and I hope help, computational technology change what we can learn about our Universe. Today, in 2025, I somewhat unexpectedly find myself involved in a broad range of AI-based and AI-enhanced efforts designed to speed learning and discovery in astrophysics and in science. In this talk, I will offer glimpses into a handful of ongoing AI-enhanced efforts, each of which is very different from the others, yet which work together in a researcher/educator's life to speed progress. Work to be highlighted includes: 1) automated **data-set linking** in the "glue" and LIVE-Environments visualization environments; 2) The **"Reading Time Machine"** which uses AI to "read" graphics and images and ingest their content into the ADS Literature archive, as "data," 3) approaches to **3D selection** in volumetric data, using both AI and augmented reality (AR); 4) a quest to understand why LLMs are so good at describing **infographics**, but so terrible at creating them; 5) capabilities of AI for writing **code for visualization**, in both research and education. The plan of the talk will be to present an overview of each of these efforts, in order to inspire broader discussion of whichever topics evolve as most interesting to the assembled audience.

Thematic questions for discussion

1. visualization and infographics — how good is AI at abstraction, and how good will it become?
2. If we give “all” the MilkyWay3D.org data to AI, what (kinds of) new physical insights might we expect— should we have expectations *a priori*—or is that approach too restrictive? (Note, 3D dust also AI!)

AI in my Astro + Visualization Life Today

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Abstraction?

Why can't LLMs make Informative Infographics in Astronomy?

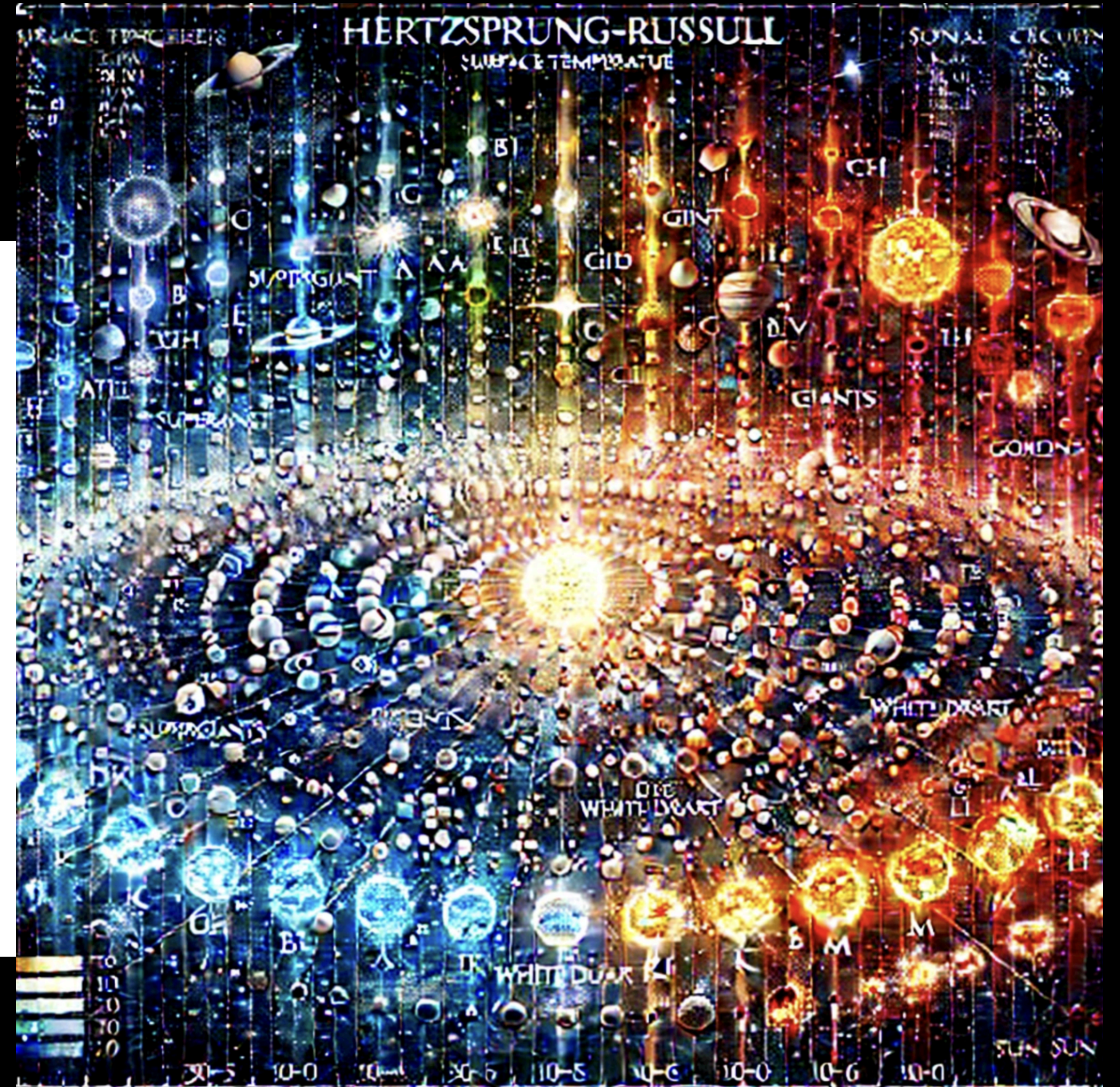
Bruna Biz

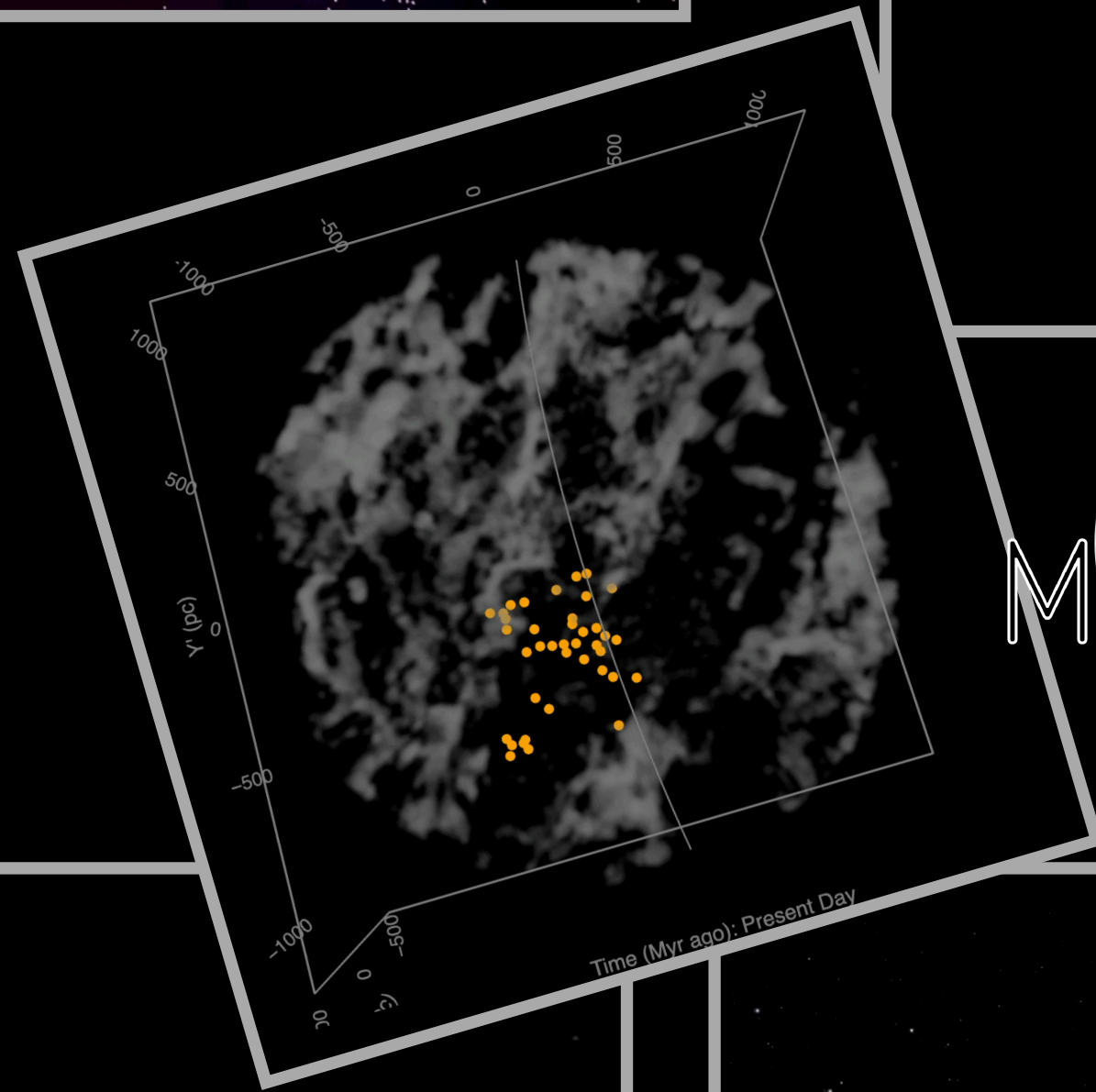
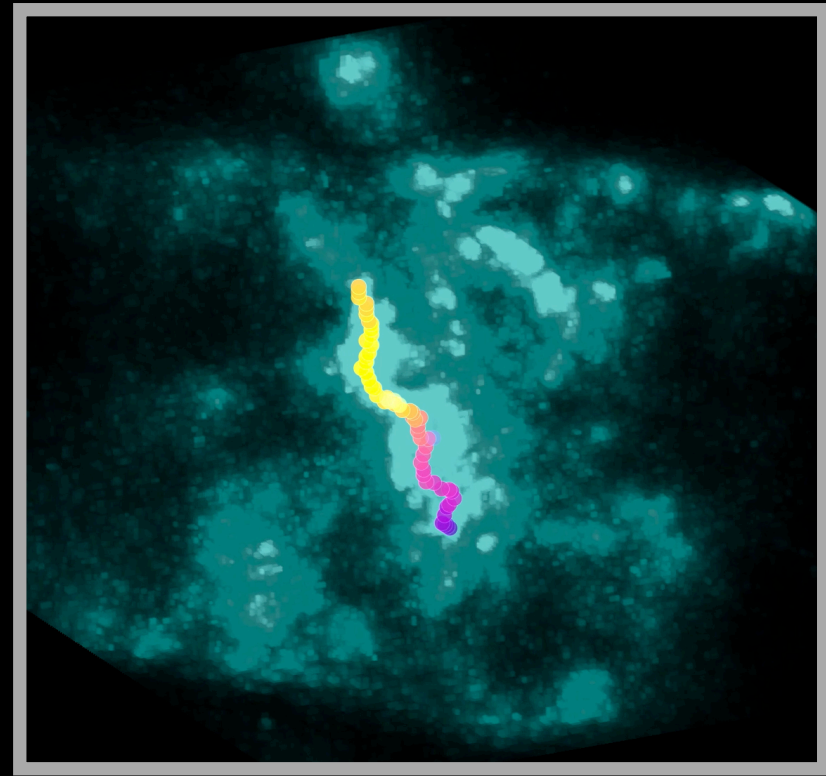
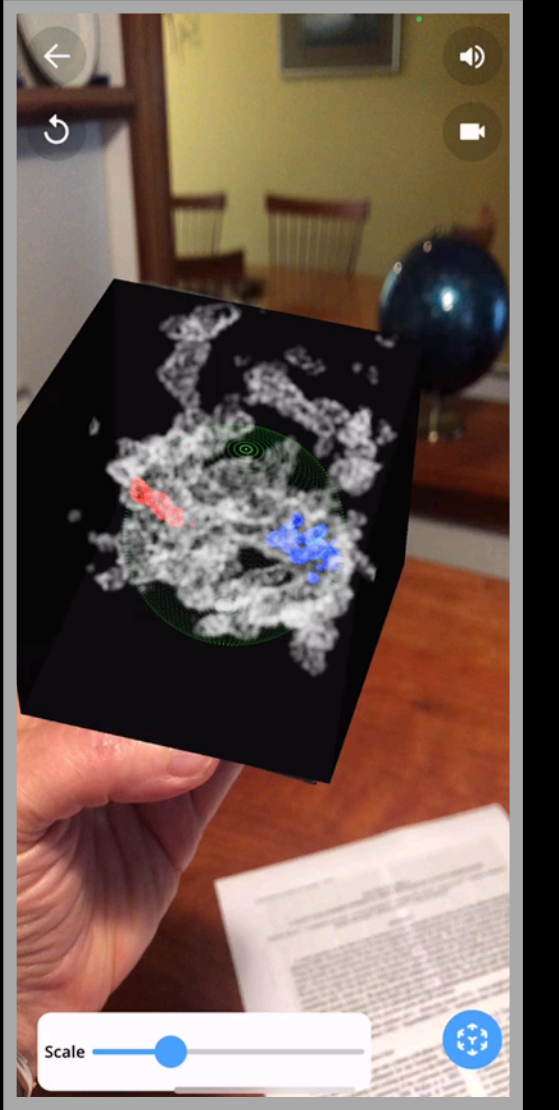
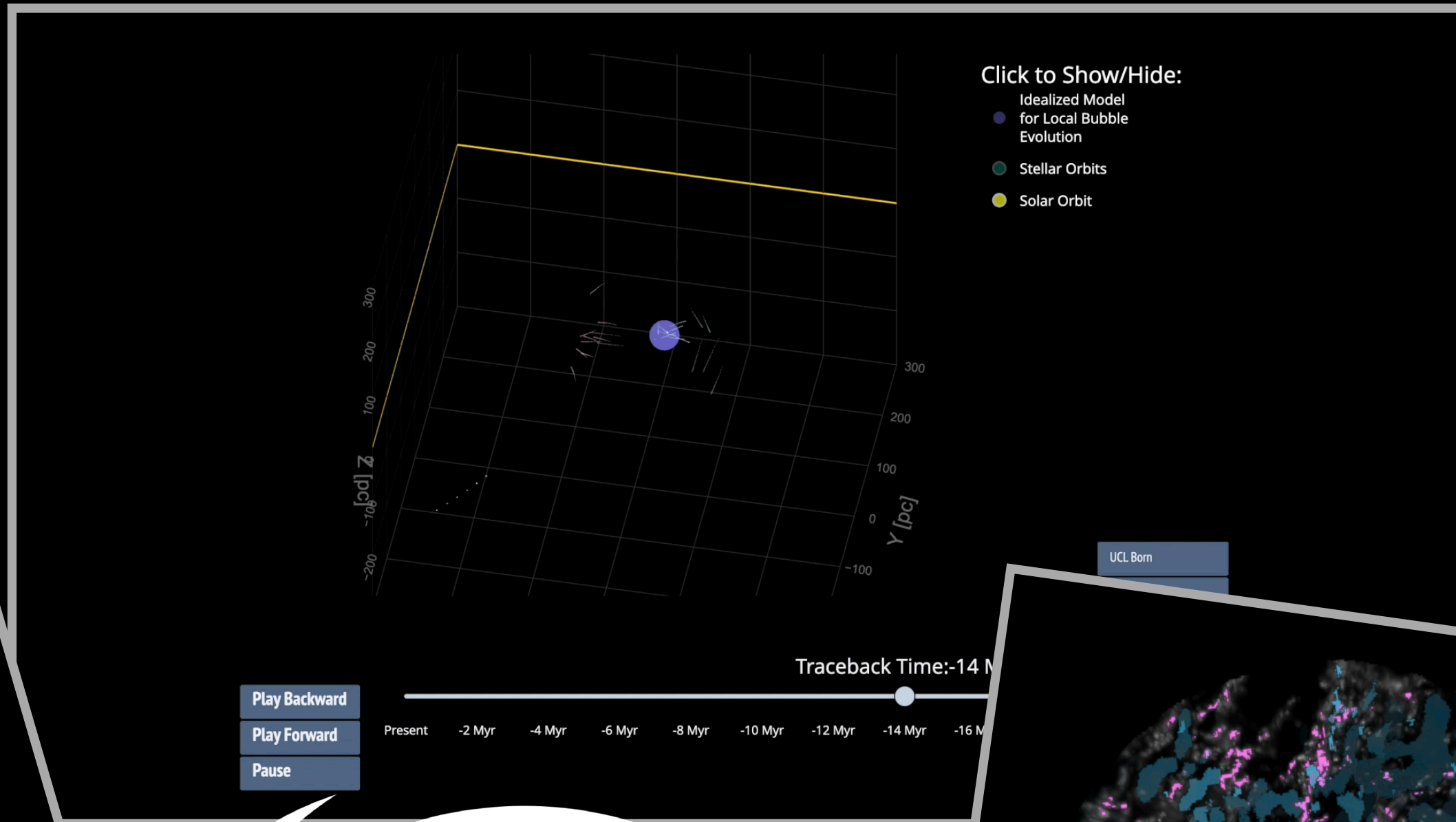
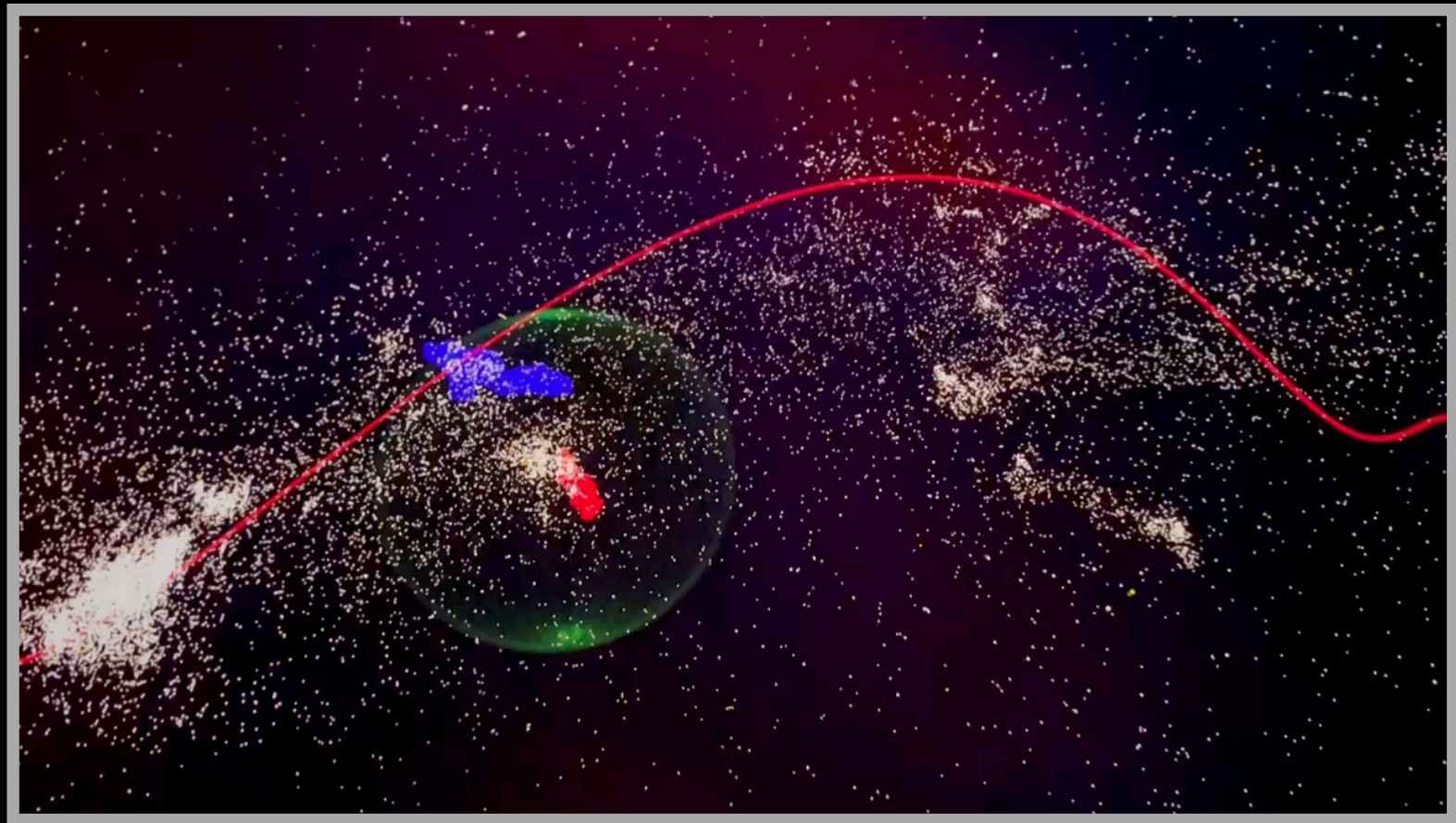
Harvard University

ABSTRACT

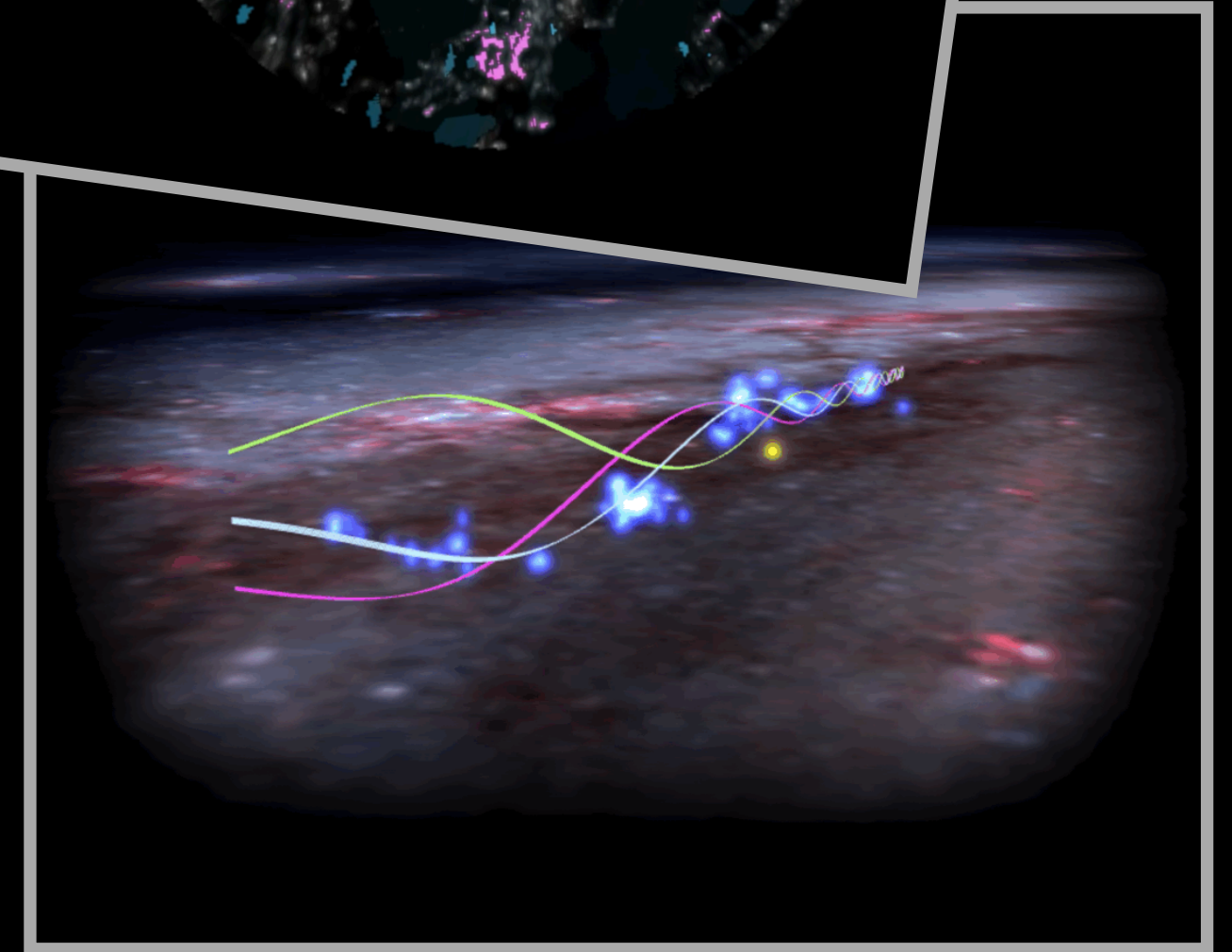
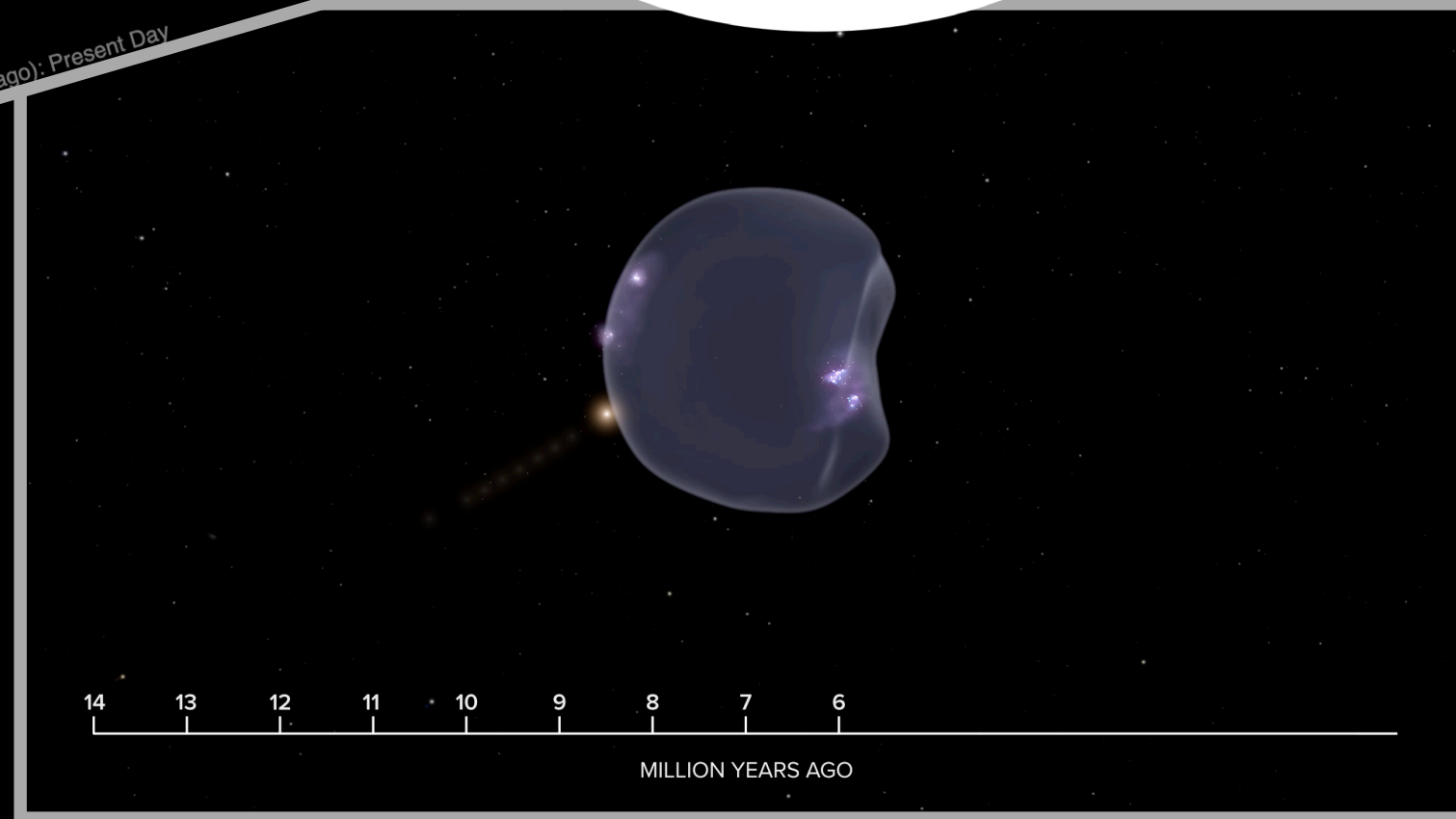
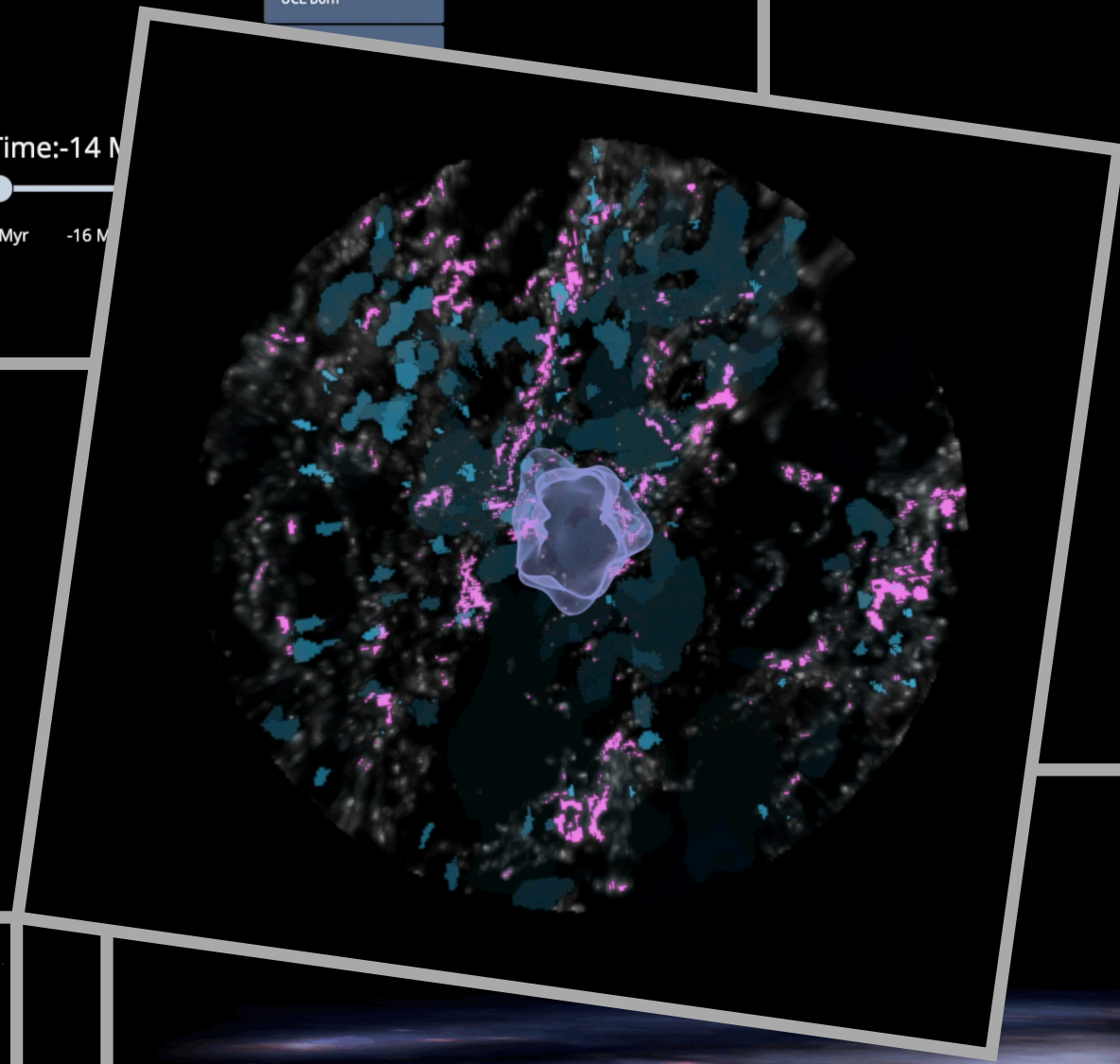
This work is designed to gauge the limitations of generative AI models such as ChatGPT and DALL-E in their ability to accurately produce astrophysical information graphics. We use the Hertzsprung-Russell (H-R) diagram – a fundamental tool in astronomy that maps the relationship between stellar luminosity and temperature – as a test case because of its simple 2D structure and its importance in stellar astronomy. Initial attempts to produce accurate H-R diagrams with ChatGPT led to interesting results which demonstrate the models' tendency to perceive and illustrate cycles (in this case, the stellar life cycle) as circles, resulting in images that deviate from the traditional linear structure of H-R diagrams. Despite high quality H-R diagrams being fed and described to the model, these patterns persist, demonstrating DALL-E's inability to diverge from circular patterns in relation to cyclic phenomena. An investigation into DALL-E's diffusion process also suggests that a big challenge with astrophysical infographic generation is rooted in how tokens are embedded and processed within latent space – an abstract, higher dimensional space where models abstract their vector embeddings. This points to potential improvements that could be made in astrophysical infographic generation to produce more accurate visuals.

Bruna Biz's Harvard Junior Paper, 2024

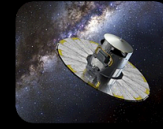




MILKYWAY3D.org

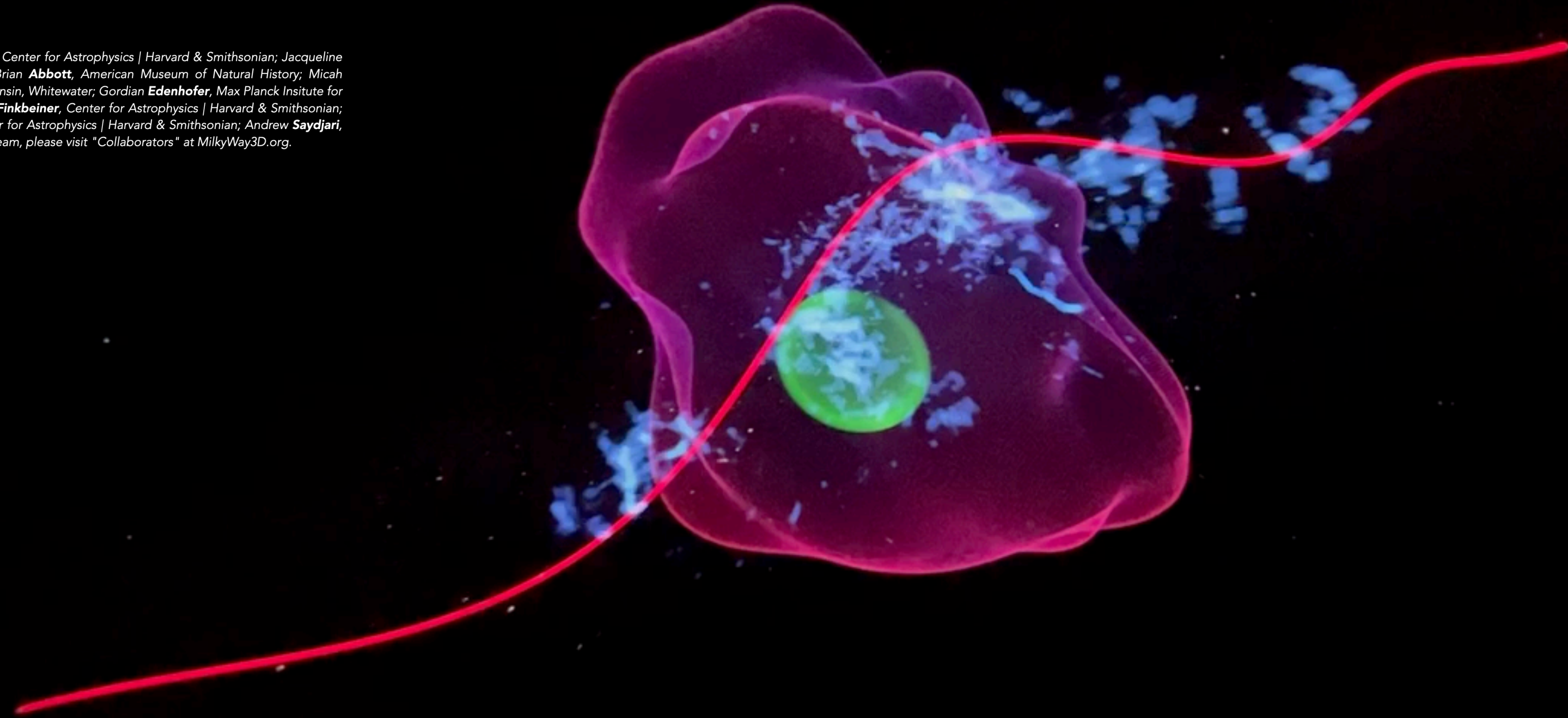


Zucker et al. 2021, Bialy et al. 2021; Zucker et al. 2022, Konietizka et al. 2024, O'Neill et al. 2024, Swiggum et al. 2024



"6D" Movie
A 3D Map of the Star Forming Milky Way, for Everyone

Alyssa **Goodman**, Center for Astrophysics | Harvard & Smithsonian; Catherine **Zucker**, Center for Astrophysics | Harvard & Smithsonian; Jacqueline **Faherty**, American Museum of Natural History; Joao **Alves**, University of Vienna; Brian **Abbott**, American Museum of Natural History; Micah **Acinapura**, American Museum of Natural History; Robert **Benjamin**, University of Wisconsin, Whitewater; Gordian **Edenhofer**, Max Planck Institute for Astrophysics—> CfA; Carter **Emmert**, American Museum of Natural History; Douglas **Finkbeiner**, Center for Astrophysics | Harvard & Smithsonian; Ralf **Konietzka**, Center for Astrophysics | Harvard & Smithsonian; Theo **O'Neill**, Center for Astrophysics | Harvard & Smithsonian; Andrew **Saydjari**, Center for Astrophysics | Harvard & Smithsonian—>IAS; and the Full MilkyWay3D.org Team, please visit "Collaborators" at MilkyWay3D.org.



June 2024 AAS Workshop on Milky Way, plus updated version Monday at CIERA!



- ### Data Collection
- Foley2022_arXiv_2212.01405_OrionShell_MW3D[HDU1]
 - Reid2019_ApJ_885_131_LocalArmFit_MW3D[HDU1]
 - Reid2019_ApJ_885_131_SGNArmFit_MW3D[HDU1]
 - Reid2019_ApJ_885_131_MW3D[HDU1]
 - Hunt2023_arXiv_2303.13424_MW3D[HDU1]
 - Lallement2019_A+A_625_A135_Split_MW3D[HDU1]
 - Edenhofer_2023_3D_Dust_XYZ_Revised-2
- ### Subsets

- ### Plot Layers - 3D Volume Rendering
- Edenhofer_2023_3D_Dust_XYZ_Revised-2
 - Zucker2021_ApJ_919_35_spines_MW3D[HDU1]
 - Bialy2021_ApJL_919_L5_MW3D[HDU1]
 - Pelgrims2020_A+A_636_A17_lmax10_MW3D[HDU1]
 - Alves2020_Nat_578_237_MW3D[HDU1]
 - Leike2020_A+A_639_A138_xyz_cube_MW3D

Attribute: PRIMARY

Limits: 5.89626e-08 0.00643762

Color:

Plot Options - 3D Volume Rendering

x axis Pixel Axis 2 [x] min/max: -73.9532 812.953 stretch: 1.00

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z axis Pixel Axis 0 [z] min/max: -54.101 593.101 stretch: 1.00

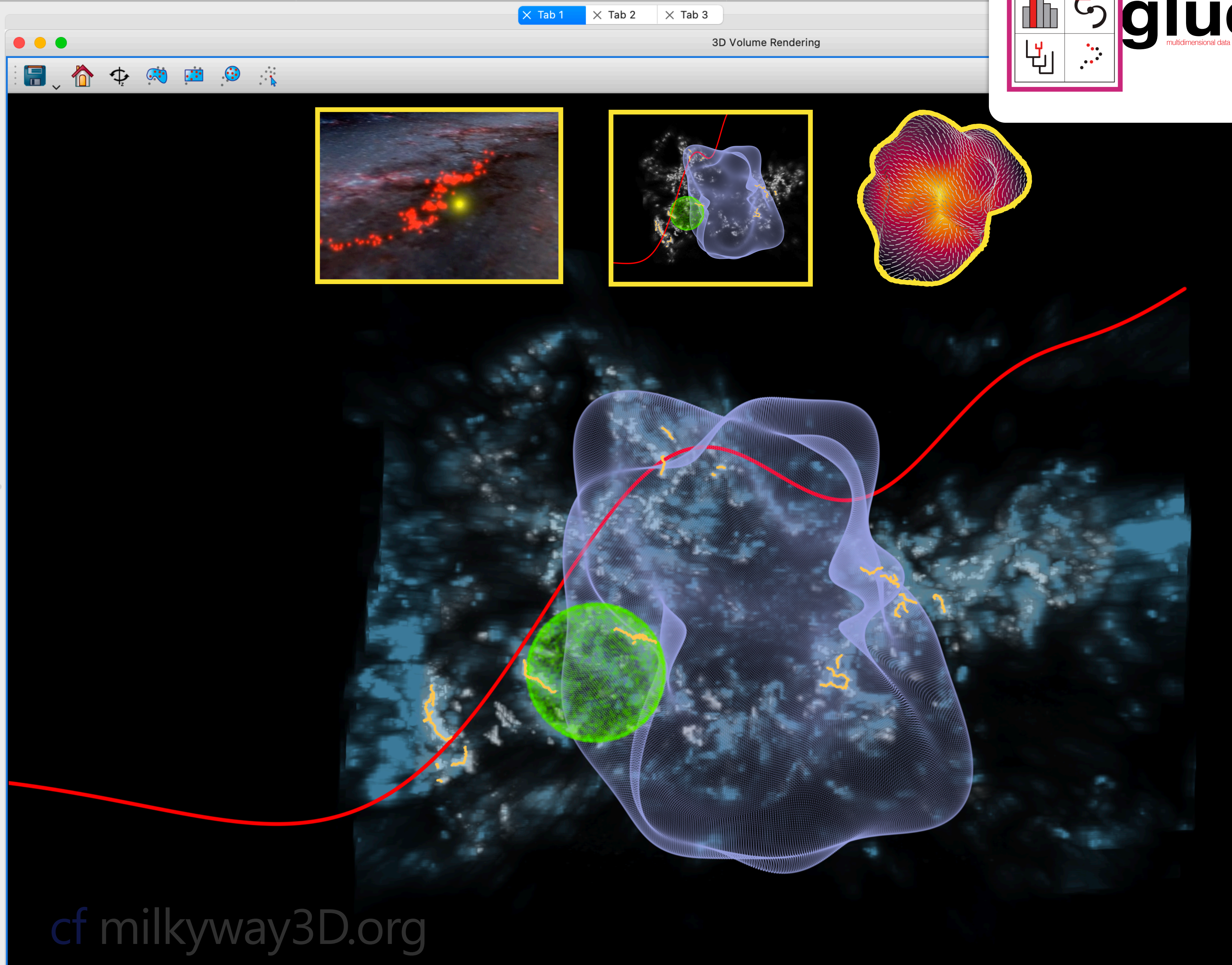
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resolution: 256

Native aspect ratio Line Width 1

Perspective Show axes

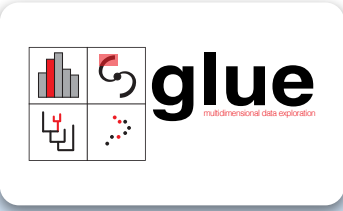
Downsample when panning





LIVE LIVE Environments About LIVE Capabilities Tech Who are we? Learn More Q

Linkable Interactive Visualization Exploration (LIVE) Environments

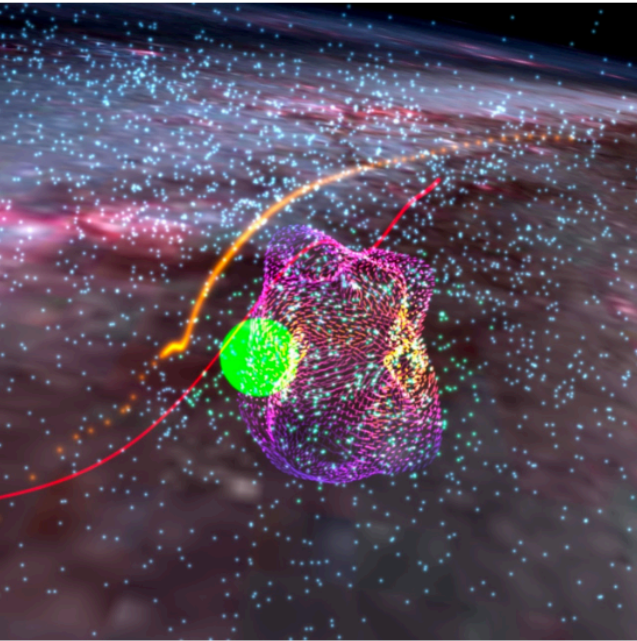


What is LIVE?


LIVE lets anyone build "Linkable Interactive Visualization and Exploration" Environments.

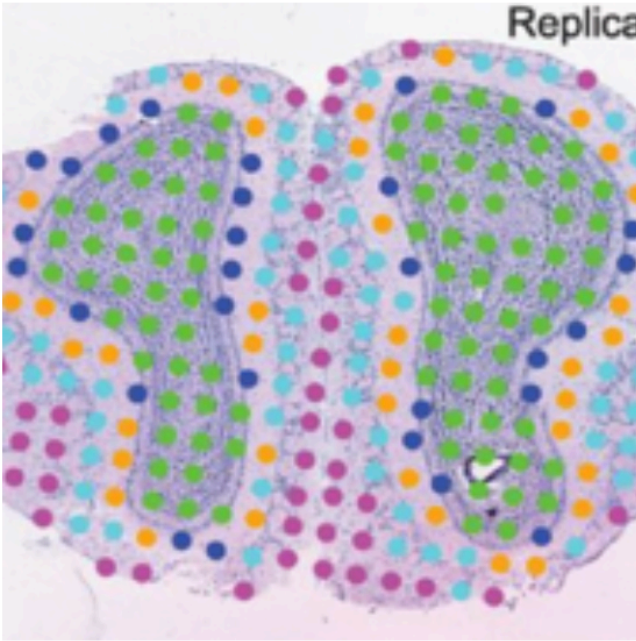
LIVE is free, open-source, and helps with shared data and visualization challenges across astronomy (LIVE Astro), biology (LIVE Bio) and GIS (LIVE GIS).

As LIVE's infrastructure is being built, collaborators are ensuring its utility across Astronomy, Biology, and GIS by pursuing LIVE's science demonstration projects.




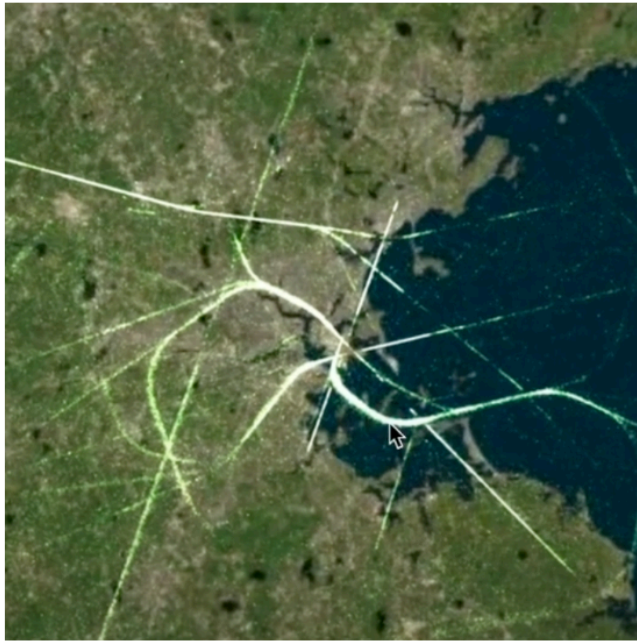
LIVE Astro






LIVE Bio





LIVE GIS



MilkyWay3D.org Home Data Software Science Gallery Events Collaborators Vienna Site (Private) Q

THE MILKY WAY IN 3D

(VI- THE SUN'S NEIGHBORHOOD)

Welcome to a new view of the Milky Way... in 3D!

With community input, milkyway3d.org will serve as a hub for the interconnected set of outreach, education, and research resources that allow astronomers to map out and understand the three-dimensional structure of the Milky Way (especially near the Sun).

The project includes new software development, approaches to data sharing, and scientific research questions propelling our collaboration forward. In fact, MilkyWay3D's tech is so innovative, that it's the "demonstration project" for LIVE-Astro, the astronomy portion of the "Linkable, Interactive, Visualization, & Exploration" or "LIVE" Environments project.

All data sets and software collected, connected, and created will be available to all--including educators and learners!

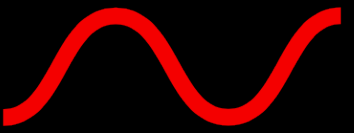
Debut in Pasadena

The first time the MilkyWay3D.org was presented to the astronomy research community was at the [Surveying the Milky Way: The Universe in Our Own Backyard](#), in the poster shown here, and in talks by Science PI Catherine Zucker and Harvard graduate student Theo O'Neill.

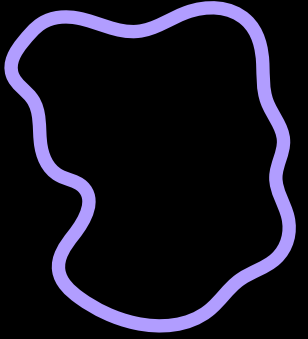


The poster features the MilkyWay3D.org logo and the text: "Welcome to a new view of the Milky Way... in 3D! MilkyWay3D.org is an open-data open-source discovery hub, providing data, visualization, and research tools for studying the Milky Way in 3D." It also includes three columns: "INFRASTRUCTURE" (assembling data as a community, using modern, open-source practices), "SCIENCE" (enabling studies of how galaxies turn gas into stars, using... stellar positions, clusters, motions), and "EDUCATION & OUTREACH" (connecting real research data, software, and science to learners). Logos for glue, OpenSpace, and other partners are visible at the bottom.


5 years ago, no one knew that...



There is a giant (2.7 kpc-long) “wave” of star-forming regions (Alves et al. 2020, named “**The Radcliffe Wave**”) waving up & down ($P=90$ Myr; Konietzka et al. 2024) along the “Local Arm” of the Milky Way, the Sun passed through it ~ 13 Myr ago (Maconi et al. 2024*); and a magnetic field runs along it (Panopolou 2024*).



Nearly all star forming regions within 250 pc of the Sun lie on the “surface” of the **Local Bubble** (Zucker et al. 2022), which is actually a Local Chimney (O’Neill et al. 2024*), and we can estimate what its B-field looks like, in 3D (O’Neill et al. 2024*).



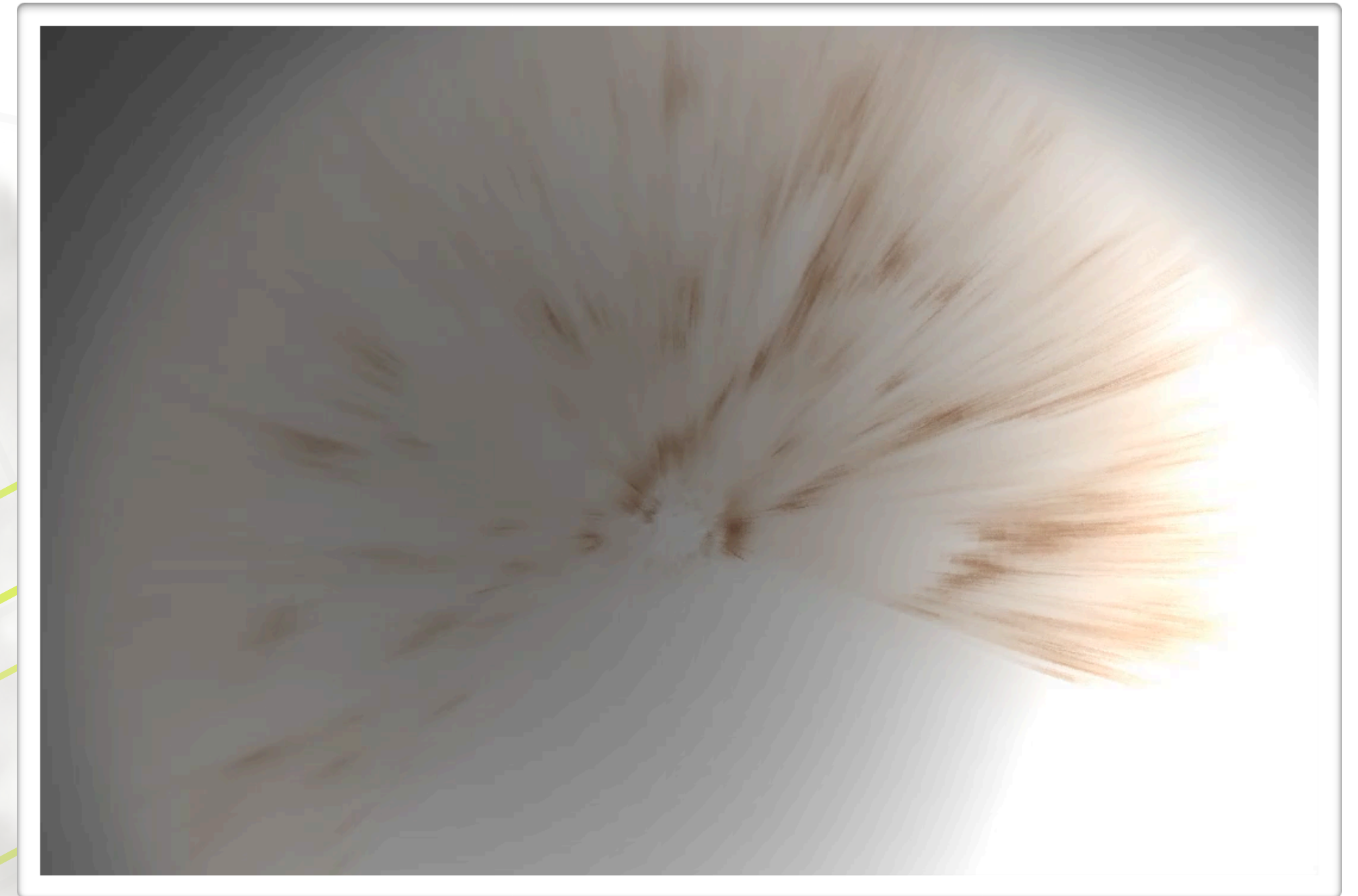
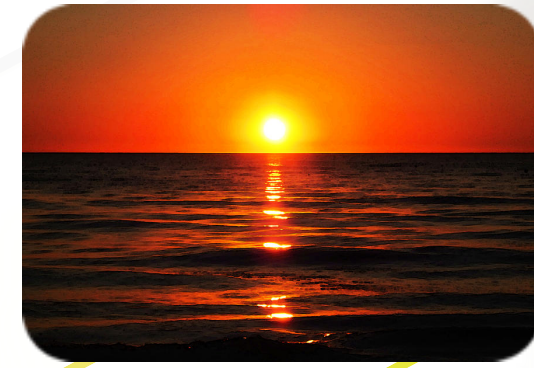
The Perseus and Taurus star-forming regions lie on opposite sides of a “shell,” with Perseus in the Radcliffe Wave, and Taurus smooshed between the Local Bubble & the “**PerTau Shell**” (Bialy et al. 2021).



“Most nearby young star clusters formed in three massive complexes” (Swiggum et al. 2024*).

**submitted, embargoed, or in prep, ask for details*

Extinction & Reddening, from Color Imaging



Green et al. 2019

Can infer matter's distance from *dust's* effects on stars.



WARNING: schematic diagram, **NOT** to scale (credit A. Goodman, 2019)

Abstraction: Why SO bad? →

Why can't LLMs make Informative Infographics in Astronomy?

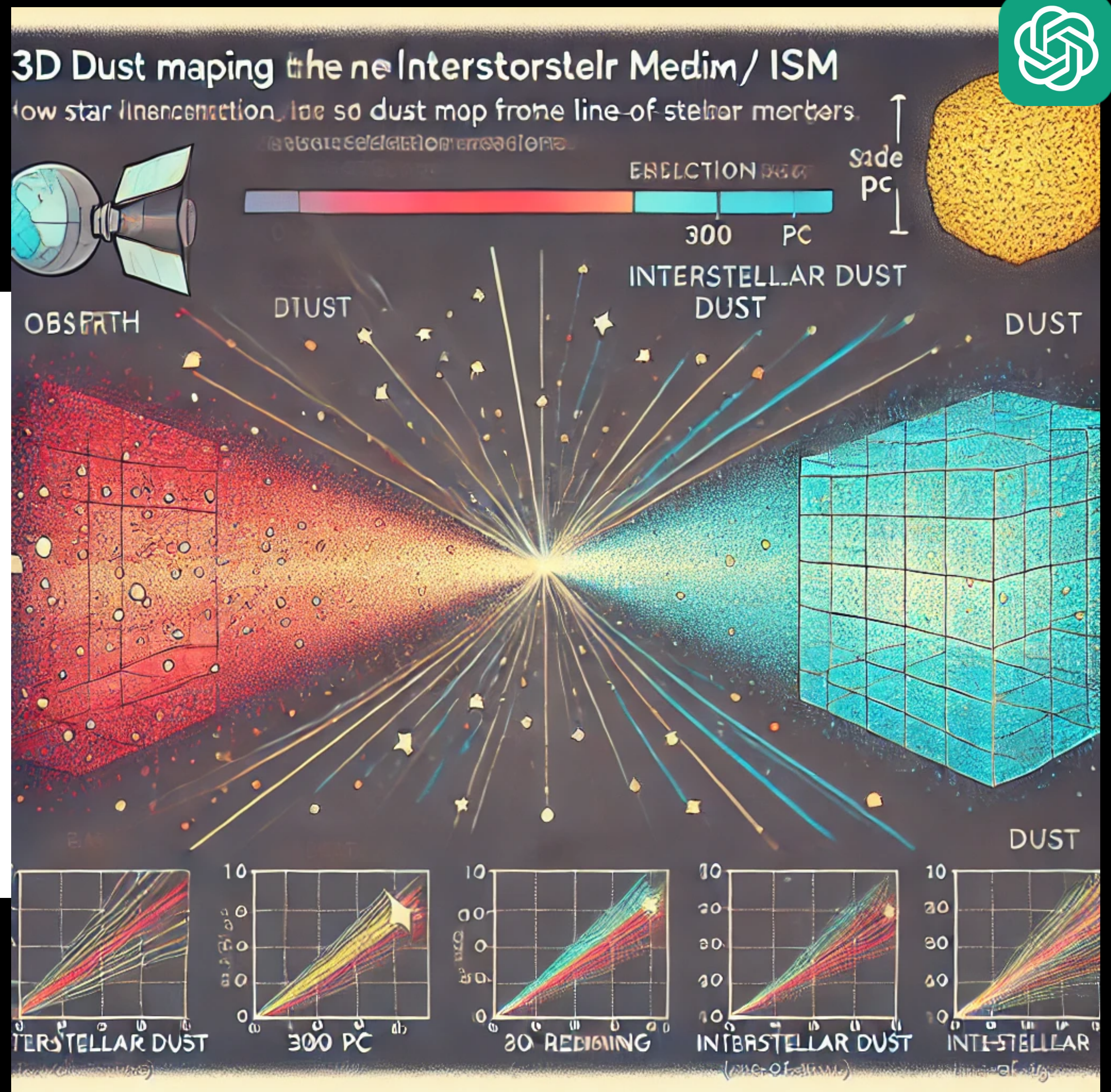
Bruna Biz

Harvard University

ABSTRACT

This work is designed to gauge the limitations of generative AI models such as ChatGPT and DALL-E in their ability to accurately produce astrophysical information graphics. We use the Hertzsprung-Russell (H-R) diagram – a fundamental tool in astronomy that maps the relationship between stellar luminosity and temperature – as a test case because of its simple 2D structure and its importance in stellar astronomy. Initial attempts to produce accurate H-R diagrams with ChatGPT led to interesting results which demonstrate the models' tendency to perceive and illustrate cycles (in this case, the stellar life cycle) as circles, resulting in images that deviate from the traditional linear structure of H-R diagrams. Despite high quality H-R diagrams being fed and described to the model, these patterns persist, demonstrating DALL-E's inability to diverge from circular patterns in relation to cyclic phenomena. An investigation into DALL-E's diffusion process also suggests that a big challenge with astrophysical infographic generation is rooted in how tokens are embedded and processed within latent space – an abstract, higher dimensional space where models abstract their vector embeddings. This points to potential improvements that could be made in astrophysical infographic generation to produce more accurate visuals.

infographics



Science in culture

Books & arts

Will AI jeopardize science photography?

Generative artificial-intelligence illustrations can be helpful, but fall short as scientific records. **By Felice Frankel**

One of the privileges of being on the campus of the Massachusetts Institute of Technology (MIT) in Cambridge is seeing glimpses of the future, from advances in quantum computing and energy sustainability and production, to designing new antibiotics. Do I understand it all deeply? No, but I am able to wrap my head around much of it when I am asked to create an image to document the research.

The joy of being a science photographer is that I must learn about the things I am documenting to produce communicative and trustworthy images, intended as a form of data, for the researchers who welcome me into their laboratories.

But now, with the wide availability of generative artificial intelligence (genAI) tools, lots of questions must be asked. Will there be a point at which, with just a few keystrokes and prompts, a scientist can create a 'visual' of their research, as I do with my camera, and consider that image a record of the work? Will research-



Iron particles in an oil drop on a glass slide respond to magnets placed underneath.

THREE VIEWS

Decisions made during the imaging process result in distinct representations of vials containing fluorescing nanocrystals. The photographs of the real vials contrast sharply with a visual created by prompting an artificial intelligence (AI) program.



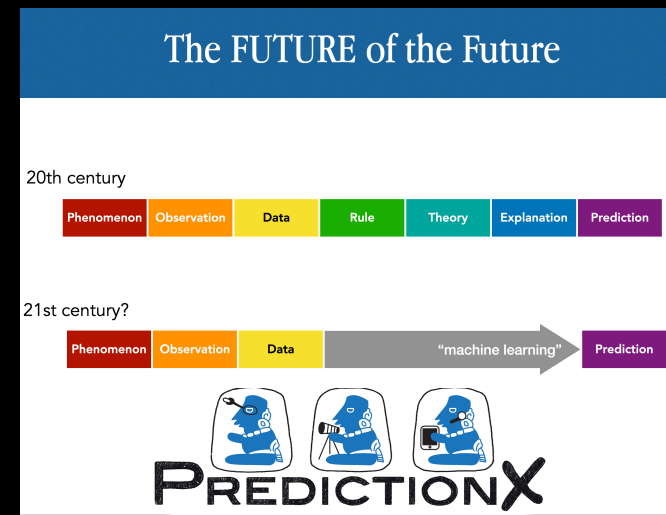
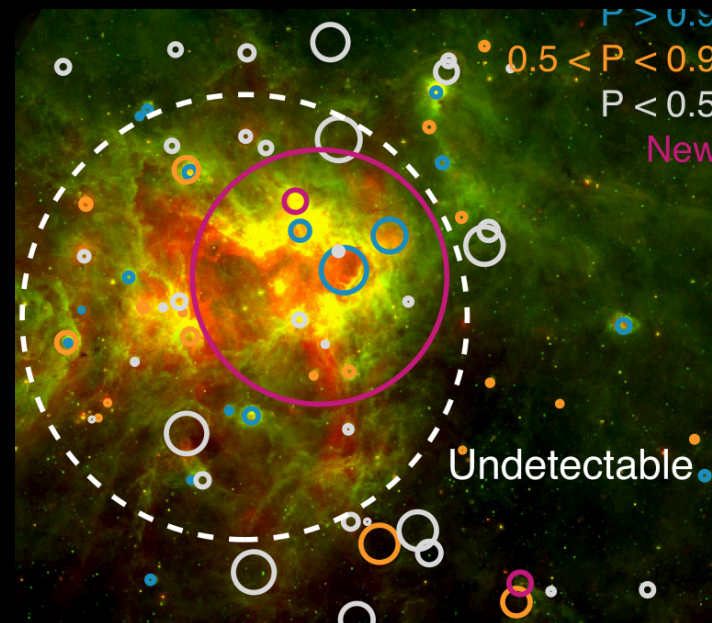
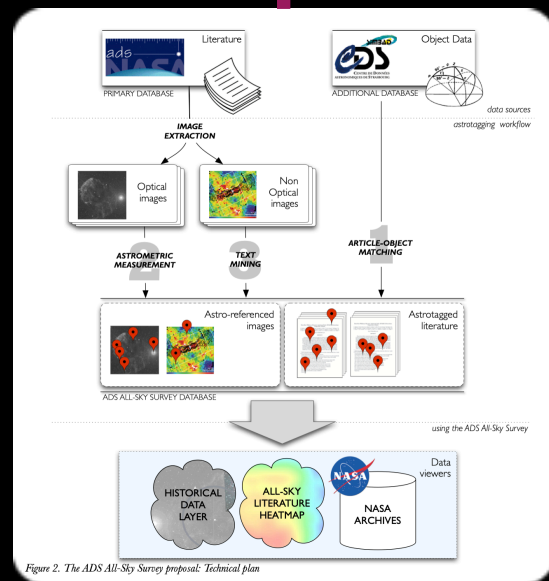
Thematic questions for discussion

1. visualization and infographics — how good is AI at **abstraction**, and how good will it become?
2. If we give “all” the **MilkyWay3D.org** data to AI, what (kinds of) new physical insights might we expect—should we have expectations *a priori*—or is that approach too restrictive? (Note, 3D dust also AI!)

Please feel free to ask me about these...

"Reading Time Machine"

code for visualization

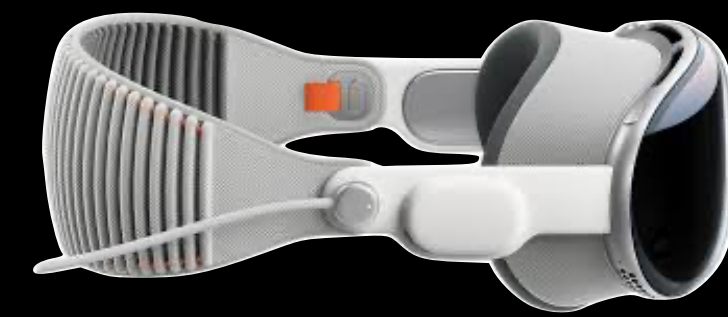
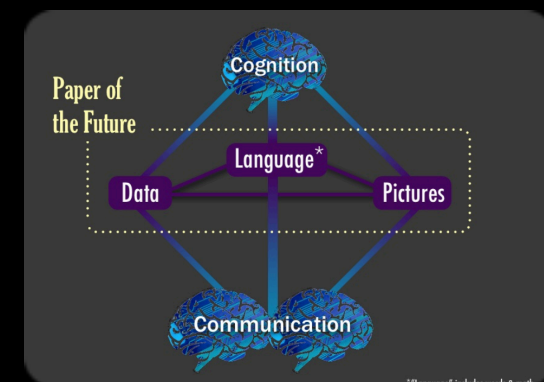
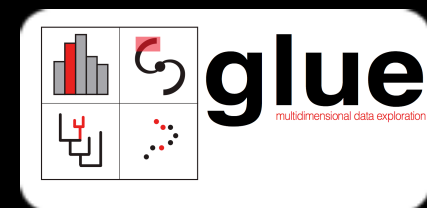


Reading Time Machine

OCR-Ground Truth Dataset
Learn more about the ~200M+ character OCR-ground truth Astronomy literature dataset.
OCR LaTeX mining interactive plots



2012 — 2014 — 2016 — 2018 — 2020 — 2022 — 2023 — 2024 —



data-set linking

3D selection

infographics

How 3D dust mapping does/does not use AI

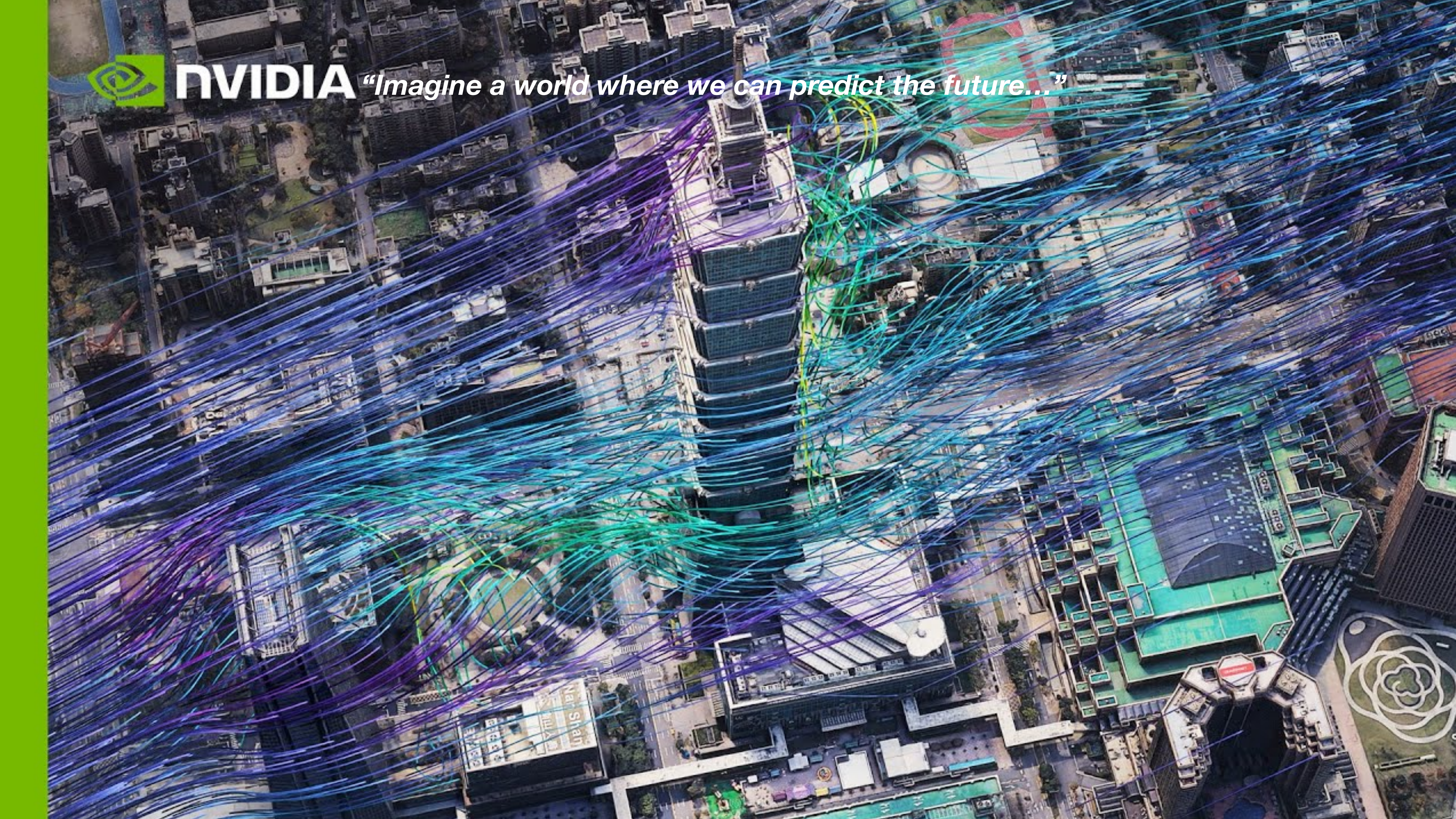


Method	Technique	AI Involvement?	Key strength
Bayestar	Bayesian inference (classic)	✗ No	Statistical rigor; simplicity
Brutus/Augustus	Advanced Bayesian inference	✗ No	Enhanced stellar modeling; precise handling of uncertainties
IFT (Enßlin)	Bayesian inference + AI	✓ Yes	Learned priors; better efficiency
Gaussian splatting	Neural rendering (AI-enhanced)	✓ Yes	Real-time visualization; realism



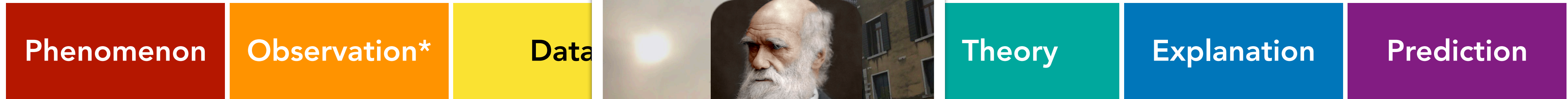
NVIDIA

"Imagine a world where we can predict the future..."

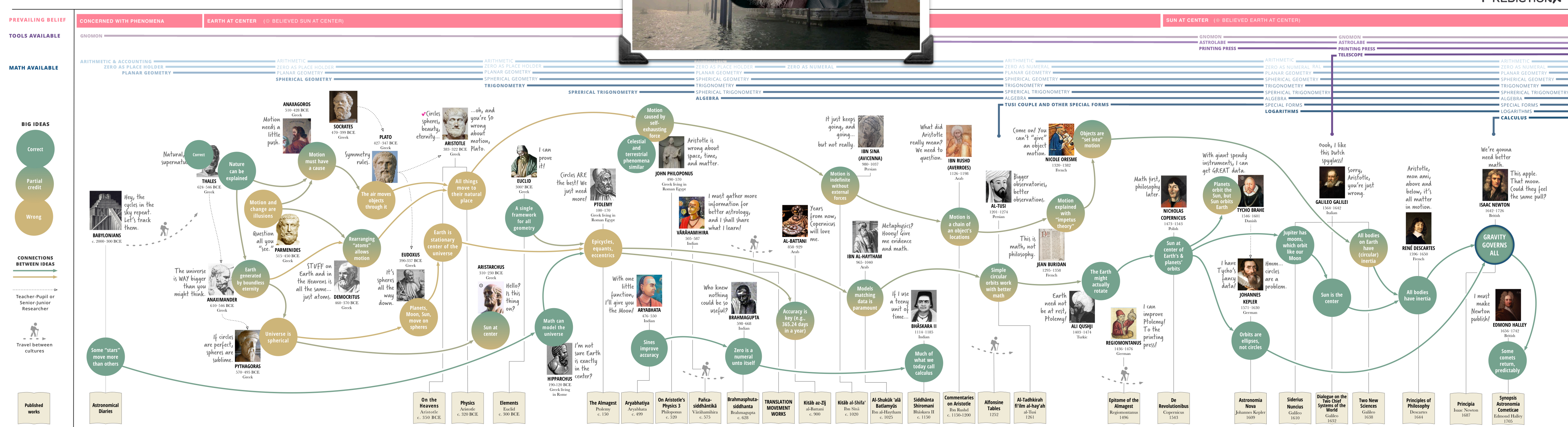


The "Padua Rainbow" & The Path to Newton

PREDICTIVE SYSTEMS



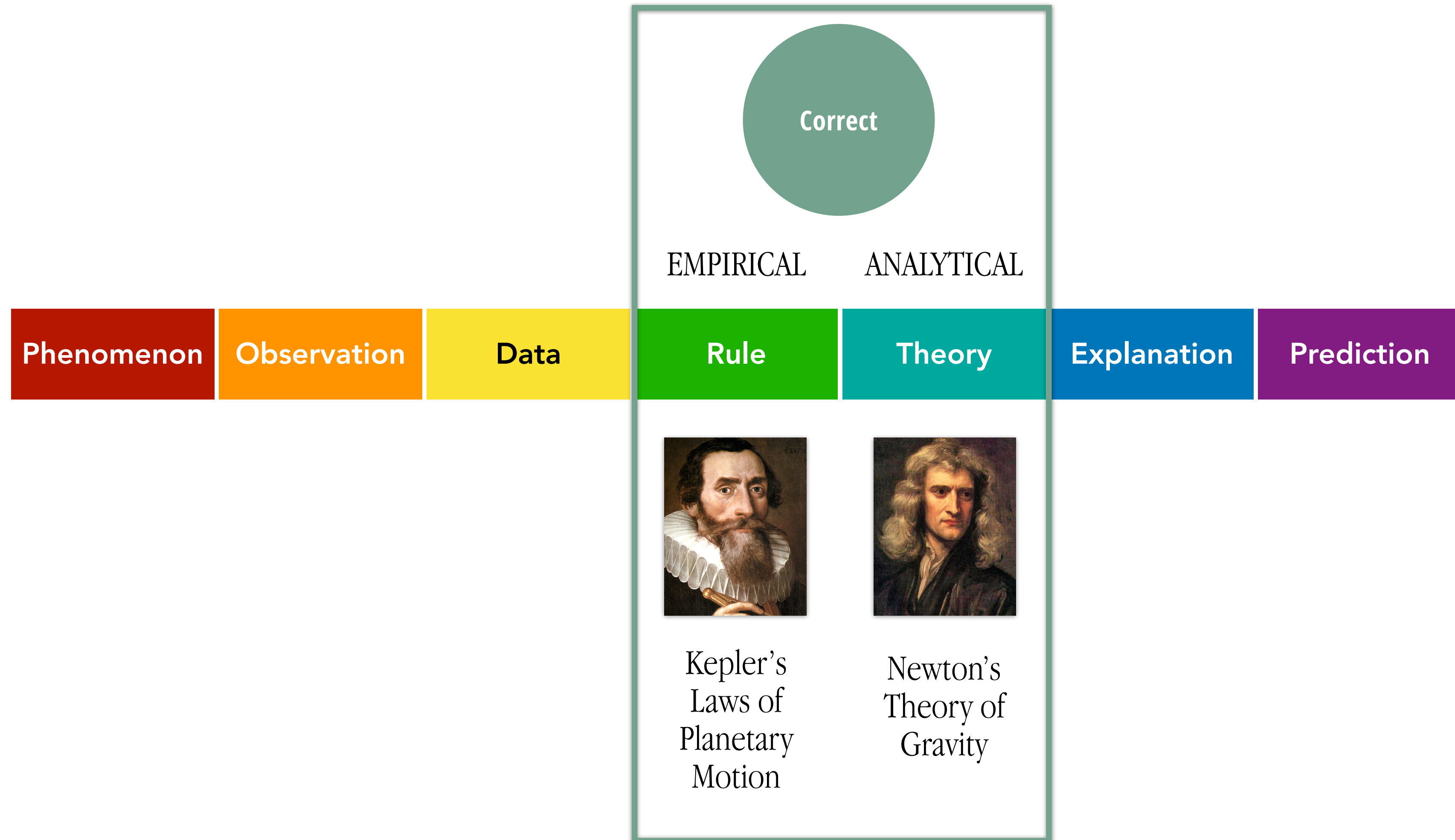
The Path to Newton



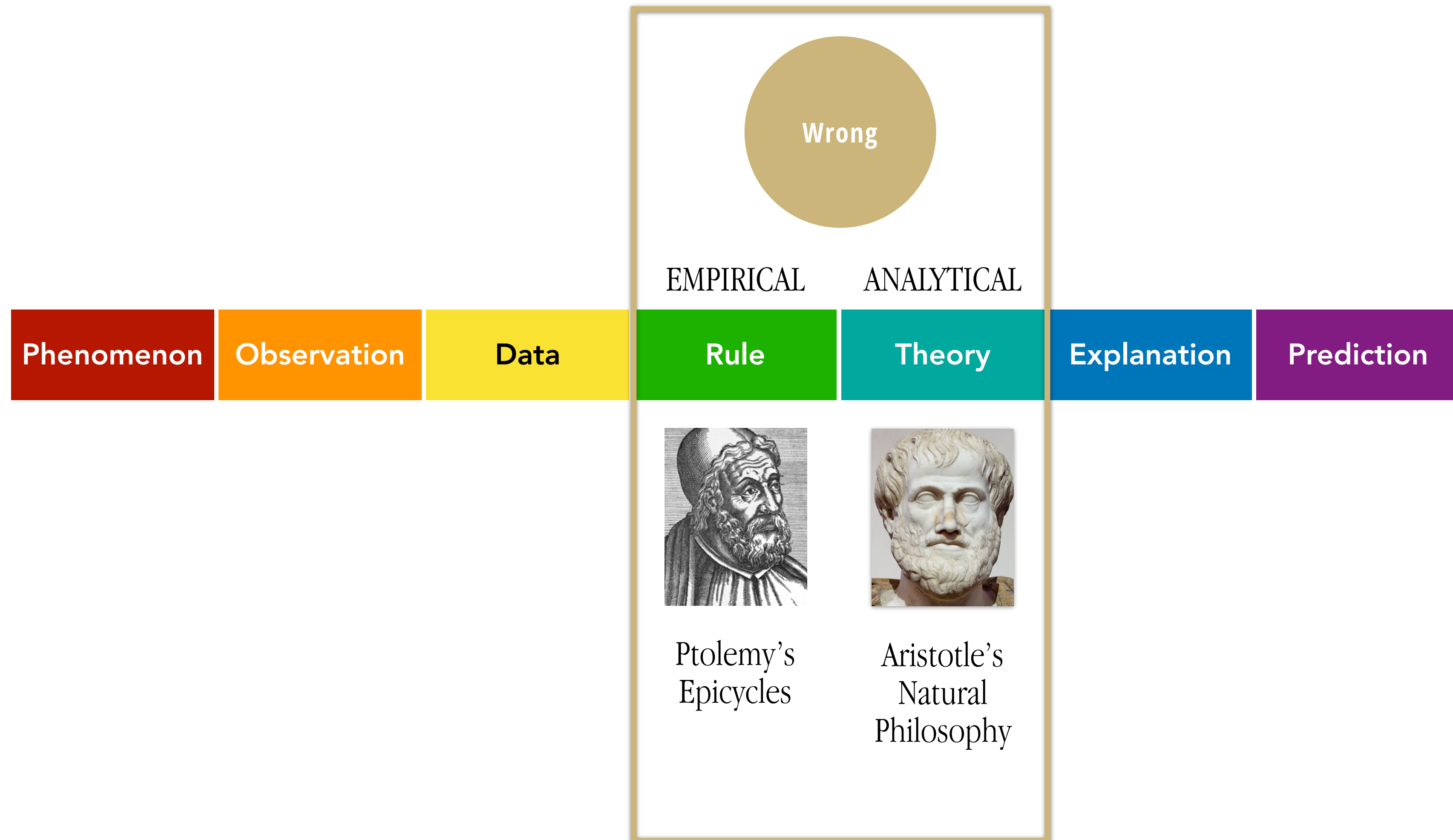
or, Experiment

© Harvard University, created by Alyssa Goodman, Jais Brohinsky, Drew Lichtenstein & Katie Peek, re-use is allowed, with attribution, version 1, 2019

The “Padua Rainbow” & The Path to Newton

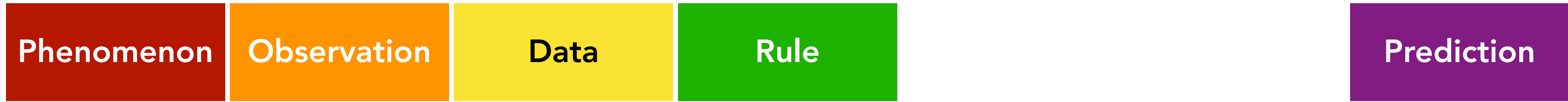


The “Padua Rainbow” & The Path to Newton





Mendel



Darwin

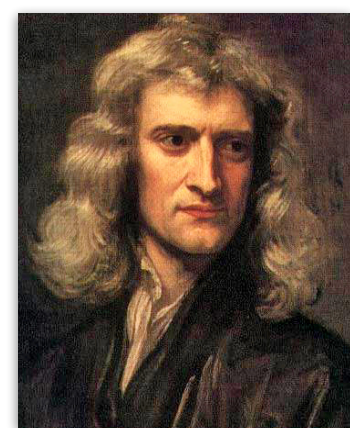


BIOLOGY

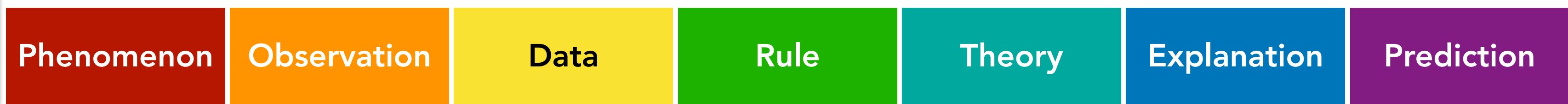
PHYSICS



Kepler



Newton





Mendel

1865

Phenomenon

Observation

Data

Rule

Prediction



Darwin

1859

Phenomenon

Observation

Data

Theory

Explanation

Prediction

NO FULLY PREDICTIVE GENERAL THEORY

FULLY PREDICTIVE GENERAL THOERY



Kepler

1609

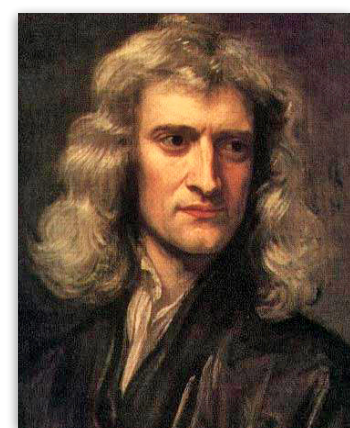
Phenomenon

Observation

Data

Rule

Prediction



Newton

1687

Phenomenon

Observation

Data

Rule

Theory

Explanation

Prediction

The Paths to Science

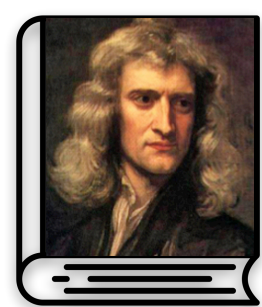
Science is so much more than equations and lab coats. It requires human creativity, ingenuity, argument, and persistence.

The goal of the Paths to Science is to deepen students,' scientists,' and the broader public's appreciation of science by telling stories of its history.

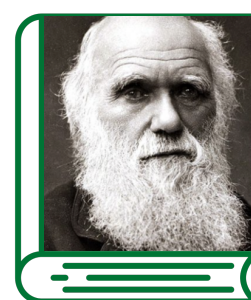
5 small books published by MIT Press, each including a narrative linked to a poster



The MIT Press



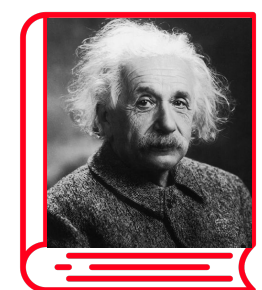
The Path to Newton



The Path to Darwin



The Path to AI



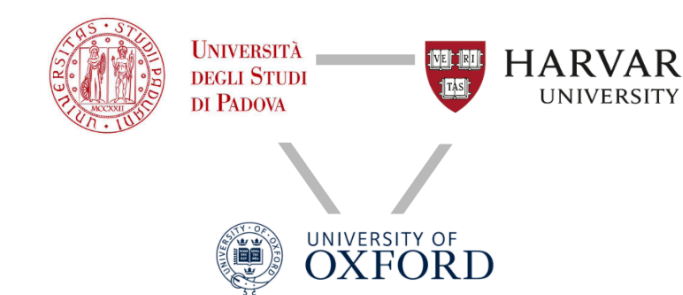
The Path to Einstein



The Path to Modern Genetics

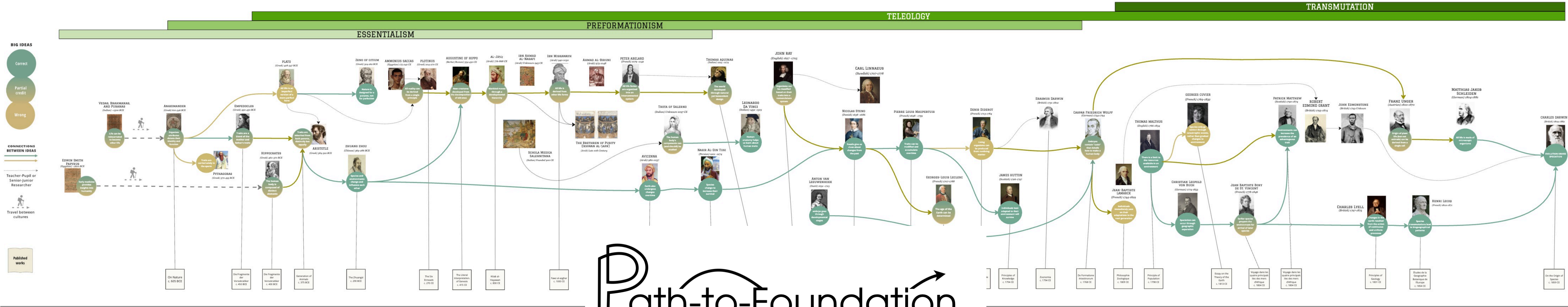
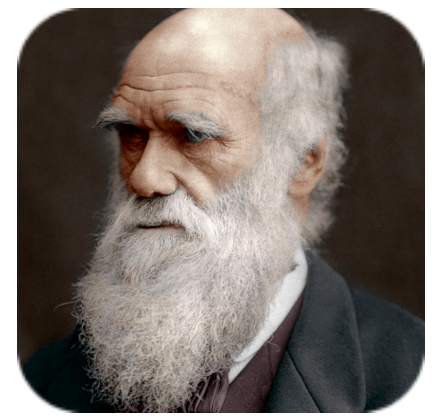
A growing consortium...

The Path-to Science Consortium



The Path to Darwin, v. 0.1

Prof. Immaculata De Vivo & Mally Shan (Class of 24)



The Path to AI, v. 0.01

Simeon Sayer, Class of 22



Path to AI Threads - Data

- Papyrus Scrolls (3000 BCE)
- Clay Tablets (2000 BCE)
- Parchment and Vellum (200 BCE)
- Invention of Paper (105 CE)
- Printing Press (1440)
- Card Catalogs (late 19th century)
- Magnetic Tape (1928)
- Hard Disk Drives (1956)
- Floppy Disks (1971)
- Compact Disc (CD) (1982)
- Solid State Drives (SSDs) (2009)
- Cloud Storage (2006 - present)

Path to AI Threads – Human History

- Artificial beings created by Gods (1600 BCE)
- Designing mechanical humanoid figures (8th - 14th century)
- Considering the design for automotive machines (1400)
- "beginning of science-fiction" (1800s)
- AI is featured in films (1950s - present)
- AI is shown to be dangerous in films (1950s - present)

Path to AI Threads - Algorithms

- Birth of graph theory (1736)
- Boolean Algebra (1847)
- Evolution of graph theory (1845 - 1990s)
- Game Theory (1928-1944)
- Linear Threshold Unit Model (1943)
- Prediction Calculus (1956)
- Logic Theorist (1956)
- Decision trees (1970s)
- Transformer Paper (2018)

The FUTURE of the Future

20th century

